THREE PAPERS ON FINANCIAL RISK TOLERANCE AND ITS RELATIONSHIPS WITH RISK-TAKING BEHAVIORS

by

EUN JIN KWAK

(Under the Direction of John Grable)

ABSTRACT

This dissertation is comprised of three papers that examine various aspects of financial risk tolerance and its relationship with risk-taking behavior. Data were collected from diverse sources, including an experiment, nationally accessible data, and an online survey. The first paper evaluated patterns of brain waves (i.e., alpha, beta, and gamma) as descriptors of financial risk-taking behavior using quantitative electroencephalographic (EEG) data. The results indicated that brain wave activation is not directly associated with the decision to engage in financial risk-taking. Instead, the findings suggest that an individual's decision to engage in a risk-taking activity is more closely related to the person's financial knowledge, financial experience, and willingness to take risks. The second study estimated the association between household income and tobacco and alcohol use while measuring the mediation effect of risk tolerance among mid-life adults using data from the National Longitudinal Survey of Youth 1979 (U.S. Bureau of Labor Statistics). The results of the regression and mediation tests indicated that risk tolerance mediates the income effect on tobacco and alcohol use. Findings from this study show that financial management can serve as an effective education tool to reduce negative health behaviors. This study provides unique insight into the interplay between household income and health outcomes, highlighting the potential benefits of incorporating financial risk tolerance and its management into public health interventions. The third study aimed to evaluate the effectiveness of different risk tolerance assessment methods in describing the risk-taking attitudes and behaviors of financial decision-makers using data collected through online surveys. A series of ordinal regression models indicated that risk-tolerance scores derived from a scale developed using psychometric principles offered more accurate insight into a financial decision-makers' current and future willingness to take risks and portfolio choices. The findings of this study suggest that if the purpose of a risk-tolerance assessment is to gain insight into subsequent risk attitudes and investment behavior, a propensity or stated preference methodology should be considered. Overall, these three studies provide valuable descriptions of the complex relationships between financial risk tolerance and risk-taking behavior.

INDEX WORDS: Financial risk tolerance, Risk-taking behavior, Electroencephalographic (EEG), Mediator on income effect, Finance and health, Subsequent risk tolerance, Portfolio choice, Behavioral finance, Household finance.

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CHAPTER 1

INTRODUCTION

Statement of the Problem

Financial planning is an interdisciplinary field that applies financial strategies and practical tools to help household financial decision-makers achieve their financial goals by considering personal characteristics, the financial situation of the household, the socio-economic profile of the decision-maker's household, and the legal environment (Warschauer, 2002). Financial planning researchers study diverse topics, including cash flow and resource allocations, generalized household financial well-being, marriage and money, and household risk-taking behaviors (Grable & Chatterjee, 2022).

Of particular importance to those who provide financial planning services as a professional occupation is the notion of financial risk tolerance (Callan & Johnson, 2002; Chang et al., 2004; Gibson et al., 2013; Hanna et al., 2008). Financial risk tolerance is defined as the maximum amount that a financial decision-maker is willing to risk when the outcome is both uncertainty and potentially negative[1] (Grable, 2000). Financial risk tolerance is thought to be directly associated with risk-taking behavior. Risk-taking behavior is conceptualized as consciously or non-consciously controlled behavior with a perceived uncertainty about decision outcomes and the possible costs of outcomes on a financial decision-maker's physical, financial, and psycho-social

[1] Another way to conceptualize financial risk tolerance is a financial decision-maker's "willingness to trade off the possibility of incurring an almost certain small gain with the potential of making a larger gain with an equally high potential of losing wealth" (Rabbani and Nobre 2022, p. 139).

well-being (Trimpop, 1994). Many studies in financial planning have illustrated the importance of financial risk tolerance as an input into generalized financial planning and specified investment management models. Financial risk tolerance is today considered one of the most significant factors associated with descriptions of household risk-taking behaviors. Understanding and measuring the financial risk tolerance of financial decision-makers (referred to as clients [those serviced by financial planners] throughout this discussion), therefore, is fundamental to providing financial planning advice and investment management services in an optimal and appropriate manner. In order to understand a client's risk tolerance, it is important to analyze and understand how different factors are associated with financial risk tolerance and financial risk-taking behaviors. While the existing literature is replete with discussions describing generalized variable associations, the existing literature tends to be based on relatively homogenous types of data. Additionally, the methodologies employed to analyze these data tend to be based on traditional correlational models (i.e., ANOVA and regression). A need exists to expand the methodological approaches used to illustrate associations between and among variables thought to be related to the concept of risk tolerance. The next frontier of financial risk-tolerance research will likely focus on analyzing data collected in various circumstances and situations with advanced statistical techniques. This type of work is needed to more comprehensively understand the risk tolerance of financial planning clients as a descriptive process and as a predictive procedure to explain risk-taking behaviors in the everyday aspect of the lives of clients (Wong & Carducci, 1991; Yao & Curl, 2011).

The studies described in this dissertation were conceptualized around a theme—applying advanced data analytical techniques to behavioral data. This application will help financial planners and other financial advisors: (a) identify key elements of their clients' financial situation(s), (b) better understand the financial problems faced by their clients, and (c) optimize their clients' goals across diverse financial scenarios. In alignment with Valaskova et al. (2019) and Roeder et al. (2022), one expected outcome associated with this dissertation is to show how data-driven solutions can help financial planners and their clients make better decisions when faced with risky (i.e., uncertain) financial decisions. Additionally, findings from the studies comprising this dissertation will provide insight into the ways financial planners, other financial advisors, and household financial decision-makers evaluate financial situations and the financial markets. When viewed holistically, this dissertation advances the existing financial planning and financial risk-tolerance literature by describing the pathways to improve the way risk tolerance is evaluated and used in financial planning models. Although researchers have acknowledged the importance of diversifying data sources and methodological approaches to better understand clients' attitudes, behaviors, and the relationships between these two, very few studies have moved in this direction. This dissertation fills this gap in the literature by examining diverse data in financial planning (e.g., data from panel surveys and experimental data) as these data relate to household financial risk-taking behaviors.

Purpose and Justification of the Studies Comprising this Dissertation

The purpose of this dissertation is to evaluate how a financial decision-maker's financial risk tolerance and their personal characteristics are associated with risk-taking behaviors such as gambling, health risk-taking, and portfolio choice. The dissertation advanced the existing financial planning and risk-tolerance literature by illustrating how various data sources (e.g., experimental data, nationally representative public data, and panel survey data) provide greater insight into the ways financial decision-makers incorporate their willingness to take a risk into daily risk-taking behavior(s).

The dissertation is structured around the presentation of three empirical studies. The first paper, entitled “Electroencephalographic Brain Wave Patterns as Descriptors of Financial Risk-Taking Behavior,” investigates whether brain activation is directly associated with the choice to engage in financial risk-taking behavior. The study examined experimental data collected in the Financial Planning Performance Lab at the University of Georgia. Data utilized a combination of direct survey inputs, measures from an electroencephalography (EEG) device, and engagement in a “real” risk-taking scenario.

The second paper, “The Role of Risk Tolerance as a Mediator between Household Income and Tobacco and Alcohol Use Among Mid-Life Adults in the United States,” examines the relationship between household income and tobacco and alcohol use as mediated by risk tolerance. This study utilized data from the National Longitudinal Survey of Youth 1979.

The third paper, “A Comparison of Financial Risk-Tolerance Assessment Methods in Predicting Subsequent Risk-Tolerance and Future Portfolio Choices,” investigates the relationship between the primary assessment methods used by financial planners to measure their clients’ financial risk tolerance and future portfolio allocation choices. In addition, this paper will identify differences and similarities across three measures of risk-tolerance assessment in predicting the subsequent financial risk tolerance and risk-taking behaviors of household financial decision-makers. Data for this study employed survey data from a panel study conducted at the University of Georgia in 2020 and 2021.

In addition to the dissertation outcomes already discussed, this dissertation aims to fill three unique gaps in the existing financial planning and financial-risk tolerance literature. First, few studies have tested whether self-assessed financial risk tolerance, related personal characteristics, and brain wave activation correlate with the engagement in risk-taking behaviors. The first paper examined the relationship among these elements (e.g., financial risk tolerance, personal characteristics, and brain wave activation) to address the question of whether brain wave activation is a precursor to risk-taking behavior. Second, few studies examining the mediation effect of risk tolerance on the association between household income and health-related risk-taking behaviors, such as smoking and drinking behavior, exist. The second paper shows how risk tolerance—measured across seven domains of risk tolerance—can mediate the income effect on tobacco and alcohol. The paper addresses the question of whether risk tolerance dampens or extenuates a decision-maker's risk-taking in the context of risk capacity factors. Third, almost all financial risk-tolerance studies, in the context of financial planning, tend to be cross-sectional in nature. To the author's knowledge, no financial risk tolerance panel data exist. The third study was designed to address this gap in the literature by empirically identifying the predictive power of risk-tolerance assessment methodologies in explaining subsequent-period portfolio choices. The paper provides evidence to answer the question of whether financial risk tolerance can predict the future financial risk tolerance and future portfolio choice behaviors of household financial decision-makers.

Rationale, Significance, and Need for the Studies

The following discussion highlights the rationale and anticipated significance of the three studies included in this dissertation.

Individual financial decision-makers sometimes deviate from optimal behaviors, which can worsen their financial situations (Baker & Nofsinger, 2010; Sadi et al., 2011). The causes of these deviations are hard to identify, but there is some consensus among researchers about the influence of some factors. Some researchers, for example, have examined the role of cognitive appraisals (and other psycho-social characteristics) in describing financial decision-making and risk-taking behaviors (e.g., Camerer et al., 2005; Eberhardt et al., 2019; Loewenstein et al., 2001; Rasheed & Siddiqui, 2018). Among the handful of studies that have directly assessed associations between cognitive appraisals and risk-taking, nearly all show a positive association between brain activation and behavior (Martos, 2021). It is worth noting, however, that very few previous studies have tested the direct association between brain wave activation and subsequent financial risk-taking behavior. Most studies that mention this possible association were based on brain scans of decision-makers who are presented with hypothetical scenarios and then asked to solve problems rather than the presence of real dollar incentives.

Additionally, no study, to the author's knowledge, has attempted to evaluate whether neural activations/movements are linked to financial decision-making and financial risk-taking behavior(s). This line of research, however, is important in the context of financial planning practice. Financial planners acknowledge that differences between and among clients exist. Existing literature that shows factors like income, wealth, education, and gender explain, to some degree, differences in risk tolerance and risk-taking. However, the degree of explained variance in traditionally designed models (i.e., those that use measurable demographic and socioeconomic personal and household characteristics as descriptors of risk attitudes and behaviors) tends to be low (i.e., less than 50%). The missing variance may come from factors not easily identified or measured traditionally (i.e., via observation, through a survey, etc.). It is hypothesized in this dissertation that brain activation may be a significant explanatory factor in models of risk tolerance and risk taking. Although collecting brain wave data and applying it to financial planning can be a challenging task, financial planners and other financial advisors need this type of research and outcome resources to gain a better understanding of their clients' situations. This enables them to identify the factors that influence a client's decision-making from taking the needed financial risk and implementing recommendations that can improve the client's financial well-being. The first paper in the dissertation addresses this need in the literature.

Physical health and financial problems are often intricately linked (Carr et al., 2015). The risk of falling into poor physical health, losing the ability to earn household income because of physical health issues, becoming widowed, or incurring high health care costs resulting from chronic disease, are examples of situations faced in the daily life of millions of individuals. While some health outcomes result from random events or unanticipated physical or mental health shocks, some health outcomes result from engaging in systematic behaviors. For example, some people maintain their weight through healthy eating and exercising. Others risk their physical health by smoking and drinking alcohol to excess. Smoking and drinking alcohol (i.e., drinking) are two well-known health risk behaviors that are known to result in significant later-life financial problems (Manning et al., 2013; Noble et al., 2015; Worthy et al., 2010). Negative outcomes tend to arise because smokers and drinkers substitute current income and wealth from savings towards current consumption, which then reduces later-life financial capacity. Smokers and drinkers also incur more health-related expenses, including increased insurance premiums and greater unreimbursed out-of-pocket medical expenses.

Many researchers have examined the direct or one-dimensional relationship between one's financial situation (e.g., household income) and health risk behaviors (e.g., tobacco and alcohol use) within households. However, little is known about the indirect relationship that can occur when a mediator variable is present between household income and health risk behaviors. Some tangential evidence exists suggesting that financial risk tolerance may be such a mediator (e.g., risk tolerance is closely related to household income and the engagement in sensation-seeking behavior; Rabbani et al., 2020). The second paper in this dissertation will add to the body of literature by testing the mediation effect of financial risk tolerance in describing the association between household income and smoking and drinking behavior. The second paper hypothesizes that financial risk tolerance, as a mediator, will exhibit a mediation effect on the relationship between household income and health risk behaviors. If the data support this hypothesis, financial planners, researchers, and policymakers can utilize the information presented in the paper to help current smokers and drinkers continue with their behaviors, reduce behaviors, or stop smoking and drinking behavior to improve their financial health outcomes. Risk tolerance may be a missing link in describing a pathway to better health behavior and outcomes.

Much of the existing financial planning literature shows that financial risk tolerance is one of the central factors in explaining and determining wealth accumulation over the lifespan (Droms & Strauss, 2003; Guillemette et al., 2012). The relationship between financial risk tolerance and wealth accumulation exists primarily because risk tolerance is an important input into investment planning and portfolio allocation models[2] . Those who are willing to take more risk are more likely to accumulate more wealth by earning higher returns. Those who seek financial security forfeit higher returns and thus accumulate less lifetime wealth (Hanna et al., 2008. Assessing and measuring financial risk tolerance, therefore, is one of the first data-gathering steps in the financial planning process. In the marketplace today, there are three primary financial risk-tolerance assessment methods used by financial planners, financial advisors, or researchers in practice (i.e., propensity measures, stated-preference measures, and revealed-preference tests). While many

[2] According to the regulatory guideline, financial planners are required to assess a client's financial risk tolerance before making recommendations or providing financial advices (Financial Industry Regulatory Authority, 2022).

researchers have examined each assessment method in relation to portfolio allocation decision, almost all previous studies have assessed variable associations in isolation (i.e., studies describe associations using one assessment tool rather than the three commonly used assessment tools). Little is known about which risk-tolerance assessment method predicts the subsequent risk tolerance level most accurately.[3] Stated another way, the literature is fairly silent in describing the predictive validity of commonly used risk-tolerance assessment methods. Understanding predictive validity is important because financial planning should consider each client's lifecycle stage and time horizon. These factors shape how a client needs to be saving and investing to reach their financial goals over the course of their life (Booth, 2004; Hong & Hanna, 2014). A better understanding of the advantages and disadvantages associated with various assessment techniques helps financial planners make reliable and valid professional judgments and choose appropriate analytical approaches to develop or adjust a client's investment portfolio and financial plan. The third paper presented in this dissertation addresses this gap in the literature.

Description of the Studies

The following discussion presents a summary of each paper's research questions, hypotheses, and the data analysis techniques.

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[3] Despite the general consensus being that multi-dimensional time horizon is a critical aspect in describing the outcomes associated with financial planning, less is known about the relationship between the level of financial risk tolerance and portfolio choice over time. Understanding how a client's financial risk tolerance may change over time can help financial planners and other financial advisors craft optimal recommendations that match a client's time horizon. In addition, recognizing the relationship between the level of financial risk tolerance and portfolio allocation choices across time can help inform the type of recommendations a financial planner makes when the goal of advice is to lead the client in a better direction for investment planning in terms of a consistent financial risk attitude.

Paper One

The first paper addresses the following research questions using descriptive statistics, bivariate statistics, and non-parametric association tests (i.e., Mann-Whitney U and median tests):

RQ_1. Do measures of self-assessed financial risk-tolerance/aversion and other personal characteristics correlate with engagement in risk-taking behavior?

RQ_2. Can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in a financial risk-taking activity?

Paper Two

The second paper evaluates the mediation effect of risk tolerance on the relationship between household income and tobacco and alcohol use. Figure 1.1 illustrates the conceptualization of the second paper. The conceptualization is based on a risk-taking model originally proposed by Irwin and Millstein (1986) and the concept of social vulnerability proposed by Ross and Wu (1995). The framework suggests that a number of factors act jointly to increase the probability that a person will engage in risk-taking behavior. These factors can be classified as predisposing endogenous (e.g., age, gender, etc.), predisposing exogenous (e.g., household income), and precipitating (e.g., psychological, social/environmental). Endogenous factors are characteristics unique to a person, while exogenous factors are behavioral influences that arise from outside sources. Precipitating factors refer to conditions that directly or indirectly impact behavior.

Figure 1.1 The Biopsychosocial Causal Model of Risk-Taking Behavior (Irwin & Millstein, 1986; Ross & Wu, 1995).

The following research questions were assessed in this paper:

RQ_1. The relationship between household income and tobacco use is negative.

RQ_2. The relationship between household income and alcohol use is positive.

RQ_3. The relationship between household income and tobacco use is mediated by risk tolerance (in seven domains: driving, financial matters, occupational, health, faith in people, romantic relationships, and major life change).

RQ_4. The relationship between household income and alcohol use is mediated by risk tolerance (in seven domains: driving, financial matters, occupational, health, faith in people, romantic relationships, and major life change).

The research questions were evaluated using a series of ordinary least squares regression analyses, a series of Sobel tests, and a sensitivity analysis.

Paper Three

The following research questions were examined in the third paper:

RQ$_1$. How stable is risk tolerance across periods?

RQ$_2$. What factors can be used to predict the subsequent risk tolerance of a financial decision-maker?

RQ$_3$. Which type of risk-tolerance assessment method offers the best prediction power when identifying subsequent portfolio choices?

After analyzing descriptive statistics to portray the sample, the first research question was addressed using a non-parametric correlation analysis to check associations among the risk-tolerance measures across periods. A series of ordinal regression models were conducted to answer the second and third research questions.

Summary

The purpose of this dissertation is to add to the existing literature in financial planning and financial risk-tolerance assessment by describing the relationships between financial risk tolerance and risk-taking behaviors such as gambling, tobacco and alcohol use, and portfolio allocation choices, controlling for personal and household characteristics. A unique contribution of this dissertation is the application of different data analysis techniques using a variety of data (i.e., panel data, experimental data, and nationally generalizable survey data). Findings from the three papers comprising this dissertation can be used by financial planners and other financial advisors, researchers, and policymakers when the goal is to improve households' financial well-being through appropriate behavior that matches a financial decision-maker's willingness to take risk. This dissertation adds to the literature by illustrating the importance of risk tolerance in describing, explaining, and predicting risk-taking behaviors in household finance and health domains. This dissertation describes the dynamics of risk-taking in a variety of situations that can assist financial planners (and other financial advisors) making better recommendations to a client.

In summary, this dissertation assumes that financial planners and others providing financial advice to household financial decision-makers will learn and see various cases and studies to understand their clients' situations better. Financial planners operate in a complicated world, as do their clients. This dissertation presents a variety of ways to understand the relationship between financial risk tolerance and risk-taking behaviors, emphasizing the importance of financial risk tolerance in financial planning.

The remainder of this dissertation is presented as follows. First, each of the three papers is presented as a separate chapter as each is expected to be submitted to a journal in the future. Second, findings from the three studies are summarized in the final chapter. The purpose of the summary is to provide a unified series of outcomes that can be applied by financial planners, researchers, and policymakers. The dissertation concludes with notes and a combined reference list.

CHAPTER 2

ELECTROENCEPHALOGRAPHIC BRAIN WAVE PATTERNS AS DESCRIPTORS OF FINANCIAL RISK-TAKING BEHAVIOR

Introduction

Imagine that two people walk into an investment advisor's office. In nearly all respects, these two individuals share common demographic and socioeconomic characteristics. As an example, both are of similar age and are well-educated. Now assume both individuals enter the financial advisor's office with a monetary endowment. This might be in the form of savings, an inheritance, or a gift from a relative. What happens when each person is presented with an opportunity to make a financial choice in which the outcome is uncertain and potentially negative (e.g., investing in an initial public offering)? Three possibilities exist. First, both could choose to participate in the risky activity. Second, both could opt out of the decision scenario, or third, one could elect to take the risk while the other chooses not to participate.

The choice to participate in what is, as with this example, essentially a gamble has been extensively evaluated in the literature (Charness et al., 2013). Explanations of why two otherwise similar individuals might make different choices that entail risk have traditionally been explained using either economics or a psychological lens. Someone trained as an economist would likely view the scenario as a simple risk-taking choice and then conclude that each person's choice to participate is tied to their risk preference (Mata et al., 2018). In this sense, risk preference describes the degree of variance in returns someone is willing to accept. From an economics perspective, the decision choice is associated with each person's effort to maximize utility in the context of financial constraints. Someone with psychological training would likely view the scenario a bit differently. Instead of assuming that each person's choice is linked to the goal of maximizing utility, a psychologist might argue that cognitive, attitudinal, and trait-like factors are the primary determinants underlying the choice. In this regard, the choice to engage in a risk-taking behavior is seen as only remotely associated with the decision-maker's financial capacity to engage in the behavior. Of course, elements from each argument, in all likelihood, help describe differences in choice decisions (Kahneman & Tversky, 1979). For example, it is possible that certain behavioral biases and cognitions are at play when a decision is made (e.g., the endowment effect[4]).

A third complementary explanation that some researchers use to describe choice decisions involving financial risk is essentially a neural one (Chen & Wallraven, 2017; Mata et al., 2018; Studer et al., 2013). As Rudorf et al. (2012) noted, risk preferences may reflect neural correlates of risk. Although not extensive, the extant literature shows risk preferences and risk choices appear to be associated with brain activation responses, with those willing to take risks exhibiting different prefrontal, temporal, and parietal brain patterns compared to those who present risk aversion tendencies (Gianotti et al., 2009). Rudorf and associates (2012) noted that anticipation of risk is also associated with changes in specific brain regions. Specifically, those who are risk averse—unwilling to take the risk—show strong ventral striatum and anterior insula (both of which are located deep in the brain) responses compared to risk seekers. Based on an analysis of neuroimaging scans, Rudorf et al. noted that neural activation associated with increased

[4] The endowment effect is the observation that people seem to attach additional value to things they own than what they do not own (Kahneman et al., 1990; Knetsch, 1989; Thaler, 1980).

anticipation reflects risk aversion. In other words, risk-averse people exhibit different brain than risk seekers.

Statement of Purpose

Much of the research that has explored the relationship between brain activation and risk-taking behavior has used neuroimaging technologies, primarily event-related functional magnetic resonance imaging (fMRI). While neuroimaging techniques are quite effective in (a) identifying brain activation, (b) mapping brain functioning, and (c) acquiring data about a person's executive, cognitive, and emotional functions (Blume & Paavola, 2011), this approach does suffer from disadvantages, most of which are logistical. fMRI procedures require a study participant to sit or lay still in a relatively small tube. Nusslock et al. (2015) suggested that laying in a small tube causes brain activation related to claustrophobia and associated stressors. Additionally, fMRI techniques can generate skewed data if a subject exhibit significant muscle-related episode. Finally, data collection tends to be lagged, particularly concerning hemodynamic responses. A simpler, more cost-effective technique—quantitative electroencephalography (EEG)—exists. EEG assessment techniques are widely used in clinical situations when a researcher or clinician is resource-constrained, or in situations where a study participant may be asked to engage in movement or muscle-related behavior. Additionally, EEG techniques are non-invasive and fast. Compared to fMRI, EEG allows data to be collected more efficiently and at a quicker rate (e.g., in milliseconds versus seconds of time; Nusslock et al., 2015). A limitation associated with EEG is that the technique does not offer a high-quality spatial resolution.

This study was designed to evaluate brain wave patterns as descriptors of financial risk-taking behavior using quantitative EEG. The study was set up as a quasi-experimental study to compare groups that were asked to make choices on a risk-taking task. The study did not utilize a randomized controlled trial methodology (Maciejewski, 2020). Specifically, this study was conceived as a way to assess brain wave patterns among healthy adults who were asked to (a) answer a series of financial risk-tolerance, risk aversion, risk taking, and personal characteristic questions using a computerized survey and (b) engage in a financial risk-taking game of chance. This study aimed to obtain exploratory data to provide insights as to whether engagement in a risk-taking choice scenario and risk-taking task is associated with alpha, beta, and gamma brain wave activation.

Background Review

Risk-taking is a common feature of human behavior. Risk-taking involves a complex cognitive process of evaluating options and making choices based on available information (Kohler, 1996). According to cognitive control theory, brain activity plays a key role in cognitive control and behavioral outcomes (Braver & Barch, 2002; Gonzalez-Prendes & Resko, 2012; Hammond & Summers, 1972; Zelazo & Anderson, 2013).

The relationship between neural mechanisms and risk-taking behaviors has been studied extensively in neuroscience, psychophysiology, and across a variety of biobehavioral sciences (Gratton et al., 2017). A number of researchers (e.g., Christopoulos et al., 2009; Fecteau et al., 2007; Krawczyk, 2002) have reported that individuals with high (low) levels of alpha (gamma) activity are more likely to engage in risk-taking behaviors. Cavanagh et al. (2010) noted that individuals who exhibit high alpha waves are more likely to make risky decisions in a gambling task. Numerous studies also show risk-taking behaviors are associated with certain brain lobes. Kuhnen and Knutson (2005), for example, claimed that the frontal cortex is less active when individuals take more risky behaviors. In contrast, Moser and associates (2008) argued that brain activity, measured as EEG waves, is particularly strong in the frontal and temporal regions of the brain when taking risky behaviors.

EEG recordings have captured brain wave activities in clinical settings since 1924 (Roohi-Azizi et al., 2017). EEG methodologies rely on scalp-recorded electroencephalographic oscillations, which are generated by the summation of inhibitory and excitatory postsynaptic potentials across thousands of cortical pyramidal neurons (Nusslock et al., 2015). Electrodes placed on the scalp, with each electrode corresponding to a specific brain lobe, have been shown to effectively measure these potentials. Figure 2.1 illustrates the primary location of brain lobes. Table 2.1 shows the relationship between each brain lobe and specific tasks and functions.

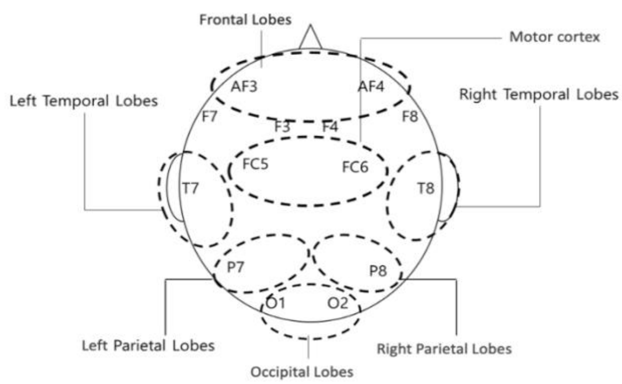

Figure 2.1. Location of Brain Lobes

Table 2.1. Brain Lobe Locations and Functions

Lobe Location	Function
Frontal lobes	Thinking, planning, memory, social awareness, and mood control.
Motor cortex	Volitional movement.
Left temporal lobes	Verbal memory, word recognition, reading, and emotion.
Right temporal lobes	Facial recognition, social cues, and object recognition.
Left/Right parietal lobes	Sensation and perception.
Occipital lobes	Visual perception.

Based on spectral analyses, EEG data is typically converted into frequency bands, which are measured as the number of pulses per second or Hertz (Roohi-Azizi et al., 2017). These bands are sometimes referred to as brain waves. Within the neuro- and psycho-physiological research community, five brain waves are typically assessed and evaluated: alpha, beta (low- and high-beta), theta, gamma, and delta. Independently and mutually, these brain waves have been found to be useful in describing human behavior in relation to specific tasks. Table 2.2 summarizes the characteristics of the five frequency bands (see Aminoff, 2012; Kropotov, 2009; Neumann et al., 2016; Nusslock et al., 2015; Rowan & Tolunsky, 2003). A key element associated with the frequency bands shown in Table 2.2 is the frequency range associated with each type of wave. For example, alpha waves are generally observed within a tight frequency range of 8 Hz to 13 Hz, whereas gamma waves are observed in a wider frequency range from 30 Hz to 100 Hz.

Table 2.2. EEG Frequency Bands

Frequency	Band	Frequency Range	Related Activity
Low frequency Waves	Delta	0 Hz – 4 Hz	Associated with dreamless sleep, most often observed in infants and young children; sometimes associated with unconscious body functions.
	Theta	4 Hz – 8 Hz	Associated with deep meditation.
	Alpha	8 Hz – 13 Hz	Related to feelings of relaxation; alpha waves are most pronounced when someone is transitioning from conscious thinking to a state of unconsciousness.
High frequency Waves	Low Beta	13 Hz – 16 Hz	Generally observed during periods of concentration and when someone is engaged in mild performing tasks.
	High Beta	16 Hz – 30 Hz	Associated with feelings of stress and anxiety; observed when someone is engaged in high energy performance tasks.
	Gamma	30 Hz – 100 Hz	Related to conscious perception and cognitive tasks.

Although each band is present, and can be measured, at all times across brain lobes, different bands dominate prior to and during specific tasks (Demos, 2005; Thatcher, 2016; Van Cott & Brenner, 1998). As illustrated in Table 2.2, brain waves can be classified as either low or high frequency. Low frequency bands (i.e., alpha, theta, and delta) are most pronounced during rest, meditation, and sleep. High frequency bands (i.e., low and high beta and gamma) are activated during periods of energy use, concentration, and mental processing (Balaz et al., 2006; Başar-Eroglu et al., 1996; Bertrand & Tallon-Baudry, 2000; Pulvermüller et al., 1997; Steriade, 2006; Thatcher, 2016; Vanderwolf, 2000). When evaluating brainwave activity, greater EEG values suggest increased brainwave activation.

The placement of scalp electrodes generally follows the International 10-20 system (Bastos et al., 2016; Roohi-Azizi et al., 2017). Under the International 10-20 system, odd-numbered electrodes refer to the left-brain regions, whereas even-numbered electrodes represent right-brain regions. Using spectral analyses and high-pass, low-pass, and notch filters, it is possible to isolate brain wave activity by millisecond (Bastos et al., 2016). In this study, brain wave data were transformed to power spectral densities (PSD) that were calculated using the following functions (see Jebelli et al., 2018):

$$S = [\ S_i(0), S_i(t=1), S_i(t=2), ..., S_j(i=T-1)],\ i = 1, ..., N \tag{2.1}$$

where T is number of data set instants with ith epoch. A covariance matrix of the vectorized form of the ith epoch [s_j = vec (S_j)] is

$$R_i(\tau) = \mathrm{E}\ [(s_i - \mu_i)(s_i - \mu_i)^T],\ i = 1, ..., N \text{ and } = 0, ..., T\text{-}1 \tag{2.2}$$

where μ_i is the mean value of the *i*th epoch. The power spectral density matrix $p_i(\omega)$ of the *i*th epoch signal at any frequency ω as the autocorrelation function is

$$P_i\,(\omega) = \sum_\tau e^{-j\omega\tau} R_i(\tau), i = 1, \ldots, N \tag{2.3}$$

The resulting dimension was μV^2 for the power and $\mu V^2/Hz$ for the power spectral density. The brain waves' power is measured by the product of 10 and the log of the micro-voltage (μV^2) squared divided by voltage fluctuations (Hz).

$$\text{Log Power Spectral Density (PSD)} = 10*\log\,(\mu V^2/Hz) \tag{2.4}$$

Specifically, frequency data were measured as Hz elicited in the frontal, parietal, and temporal lobes. The μV^2 were then divided by frequencies to estimate PSD in a format normalized with the log (E Rawls, et al., 2021; Jebelli et al., 2016, 2018; Vecchio, 2021). When measured this way, PSD indicates the strength of brain wave variation as a function of frequency. These transformed data were referred to as power bands in this study.

Research Questions

In the context of this study, the EEG measurement technique provides a direct estimation of brain response, or an event-related potential (ERP), resulting from the cognitive evaluation of and participation in a risk-taking task. Using EEG signal data obtained noninvasively and through spectral analyses, the following research questions were addressed in this study:

RQ_1. Do measures of self-assessed financial risk-tolerance/aversion and other personal characteristics correlate with engagement in risk-taking behavior?

RQ2. Can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in a financial risk-taking activity?

Methods

Sample and Procedure

Prior to beginning the study, approval for the methodology was received from the University of Georgia Institutional Review Board (Ethics Ref: PROJECT00001110). Ten individuals (five female and five male) voluntarily participated in the study. The participants were recruited from the university community. Although the number of participants was relatively small, the amount of data collected was large. Data were collected by the millisecond (i.e., 60,000 data points in one minute) over approximately 20 minutes per participants. This resulted in approximately 12 million data points for use in the analyses.

The mean age of study participants was 31 years (*SD* = 8.59 years). The demographic profile of study participants is shown in Table 2.3. Study participants were relatively young and well educated, but in other respects, diverse in sex, race/ethnicity, relationship status, employment status, housing situation, and income (i.e., household income was measured on a six-point scale ranging from 1 = less than $20,001 to 6 = Above $100,000).

Table 2.3. Demographic Profile of Study Participants

Variable	Percentage	*M* (*SD*)
Sex		
Male	50%	
Female	50%	
Age		31.00 (8.59)
Race/Ethnicity		
Caucasian/White	20%	
African American/Black	20%	

Asian	50%
Multi-racial	10%
Relationship Status	
Living with Significant Other	30%
Single	70%
Employment Status	
Part-Time	40%
Full-Time	20%
Not Employed	20%
Student	20%
Housing Situation	
Own Home	20%
Rent	70%
Live with Relative	10%
Household Income	
Less than $20,001	40%
20,001 to $30,000	10%
30,001 to $40,000	10%
$40,001 to $50,000	10%
$50,001 to $60,000	10%
$70,001 to $80,000	20%
Above $100,000	
Education	
Some College/Trade/Vocational Training	20%
Bachelor's Degree	10%
Graduate/Professional Degree	70%

As shown in Figure 2.2, the study was conducted in three stages: (1) the completion of an online survey that includes questions eliciting each study participant's willingness to take financial risk and other participant characteristics; (2) a choice dilemma after receiving a monetary endowment; and (3) the engagement in a financial risk-taking task. Specifically, study participants individually were welcomed to the research lab. Each participant was fitted with an EEG measurement device (described below). After baseline EEG data were obtained, each participant was then asked to complete the online survey. The survey process took approximately 15 minutes. Once the survey was finished, the participant was compensated with a $25 gift card. The participant then engaged in a brief discussion about risk-taking and wagering.[5] The discussion occurred in full sight of a Las Vegas-style gaming table.[6]

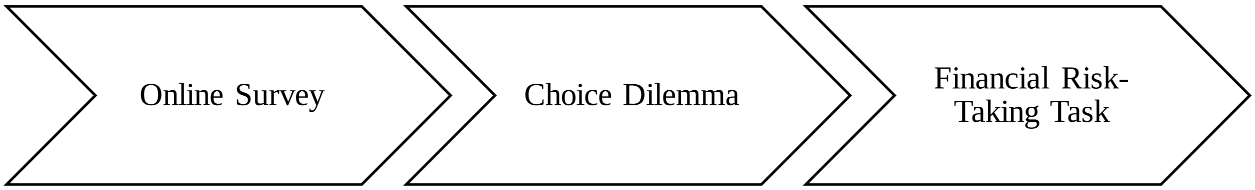

Figure 2.2. Three Stages of Experimental Procedure of the Study

This was followed by an invitation for the study participant to make a wager in an attempt to double their $25 endowment. The following statement was read:

> "At this point, you may leave the study, or you may wager your $25 and possibly leave with a total of $50 ... If you do decide to make the wager, you may lose the $25."

The wager involves engaging in a dice game where, in order to win, the participant was required to roll two dice (similar to a real craps game). To double their $25 endowment, the participant was told that they must roll a 5, 6, 8, or 9. The participant was told that if they rolled any other numbers, they would lose the amount of their wager. After a participant made a choice to engage in the risk-taking task, the following statement was read:

> "Before you roll [or leave], I would like to share the actual or true odds with you. The odds of rolling a 5, 6, 8, or 9 is 50% or 1 out of 2. Now that you know the true odds, would you like to change your wager?"

[5] To ensure consistency across cases, the author will meet with each study participant and conduct the experiment.
[6] This element of the study will be introduced as a way to make the decision-making process as realistic as possible.

Those who opted into the wager and rolled a winning number received another $25. They were then asked to sign a receipt, at which time participation was concluded. If a study participant lost the wager, they were given an opportunity to draw a colored ball from an opaque jar. The participant was told that the jar consisted of balls of two different colors (blue and white). The participant was then told that if they selected a "blue" ball, they would win back their original wager plus an additional $25. The game was manipulated so that each participant was guaranteed to select a winning ball. The same ball choice game was offered to those who elected not to participate in the risk-taking game. Although participants did not know it at the time of the study, they were guaranteed to receive $50 regardless of their risk-taking choice. EEG data were collected from each participant throughout the study process.

Equipment

An Emotiv EPOC+® EEG commercial gaming device (Figure 2.3) was used to gather brain wave data. This wireless EEG system is an effective tool in the measurement of ERPs, offering researchers a valid and reliable way to estimate brain wave data (Badcock et al., 2013). The headset measures alpha, beta, gamma, delta, and theta brain waves using a 16-point monopolar montage. The Emotiv EPOC+® EEG device provides a non-intrusive way to gather EEG signals. The device measures a person's brain waves via voltage fluctuations (i.e., Hz; Sanei & Chambers, 2013). The device uses 16 electrodes, with 14 that measure frequencies of voltage fluctuations from 14 locations on the scalp and two reference nodes (See Figure 2.1 and Figure 2.3).[7]

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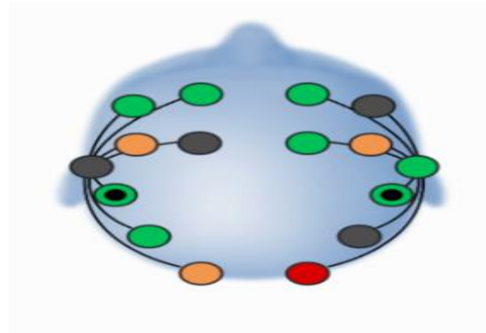
[7] In concordance with Badcock et al. (2013), one mastoid sensor will be used as a ground reference point for use as a comparison point. The other mastoid will be used as a feed-forward reference that reduces external electrical interference. As outlined by Badcock (p. 3), "The signals from the other 14 scalp sites (channels) were high-pass filtered with a 0.16 Hz cut-off, pre-amplified and low-pass filtered at an 83 Hz cut-off. The analog signals were then digitized [sic] at 2048 Hz. The digitized [sic] signal was filtered using a 5th-order since notch filter (50—60 Hz), low-pass filtered, and down-sampled to 128 Hz … The effective bandwidth was 0.16—43 Hz."

(A)



(B)

Figure 2.3. (A) EEG Headset, Emotiv EPOC+, (B) EEG Headset Placement on Scalp *(Note.* Illustration adapted from Emotiv, 2022 (https://www.emotiv.com). In the public domain*)*.

Similar to Heo (2019), in this study, brain waves from the following brain regions were measured and analyzed: left- and right-temporal, left- and right parietal, and left- and right frontal lobes. Brain waves in the parietal lobes were measured at P7 and P8. Waves in the left temporal lobes were measured at T7, whereas those in the right temporal lobes were measured at T8. Frontal lobe brain waves were measured at FC5 and FC6.

Survey

The online survey was comprised of questions designed to reveal the following study participant characteristics. These questions were used to obtain data for use of control variables in the study. Mood was assessed by asking, "How would you describe your current mood?" A 10-point scale was used with 1 = *bad mood* and 10 = *good mood*. Gambling preference was measured by adapting the following questions from Blais and Weber (2006): "How likely is it that you would bet a day's income at a casino?" and "How likely is it that you would bet a day's income at the horse races?" Both questions were used the following 10-point scale to measure participant responses: 1 = *extremely unlikely* and 10 = *extremely likely*. Financial satisfaction was measured by asking, "How satisfied are you with your present overall financial situation?" A 10-level response choice was offered with 1 = *lowest level* and 10 = *highest level.* Subjective financial knowledge was assessed by asking, “How knowledgeable are you about personal finance issues?” A 10-point scale, with 1 = *not knowledgeable at all* and 10 = *extremely knowledgeable,* was used by participants to indicate their perceived knowledge. Knowledge about casino games was used on the same 10-point scale with the following question: “How knowledgeable are you about casino games?” Financial experience was measured by asking, “How much experience do you have making financial decisions?” A 10-level response scale was used with 1 = *none at all* and 10 = *a great deal.*

Study participants were also asked several risk-related questions. Self-assessed willingness to take risks was evaluated by asking each participant to “Rate yourself as a financial risk-taker” on a 10-step scale with 1 = *much lower* and 10 = *much higher*. The stated risk preference of each participant was measured with the following single-item question from the Survey of Consumer Finances (SCF) which reads as:

> “Which of the following statements comes closest to the amount of financial risk that you are willing to take when you save or make investments?

Four answer choices were provided: (a) Take substantial financial risk expecting to earn substantial returns (coded 4); (b) Take above-average financial risks expecting to earn above-average returns (coded 3); (c) Take average financial risks expecting to earn average returns (coded 2); and (d) not willing to take any financial risks (coded 1). Financial risk tolerance was measured with the 13-item Grable and Lytton (1999) propensity measure. Scores on the scale can range from 13 to 47, with lower scores indicating *lower tolerance for risk* and higher scores indicating *greater tolerance for risk.* This measure of risk tolerance has been shown in other studies to offer valid and reliable estimates of a person's willingness to take the financial risk (Grable et al., 2014; Kuzniak et al., 2015; Rabbani et al., 2017). Constant relative risk aversion (CRRA) was assessed using the following item, which was adapted from Grable et al. (2020). The dollar amount choices linked to the question are the certainty equivalent amounts associated with the dollar tradeoffs in the question. A higher dollar amount indicates a lower degree of risk aversion.

> Suppose you are considering making an investment. You have a chance to make an investment that will return either $50,000 or $100,000. Your financial advisor estimates that the probability of receiving $50,000 is 50% and the probability of receiving $100,000 is also 50%. You also learn from your financial advisor that shares in this investment are limited and difficult to obtain. Therefore, the less you are willing to invest, the lower the chance that you will be able to participate in the investment. Based on this information, what is the largest amount of money you would be willing to pay to participate in this investment, assuming you had the money? (1) $70,711, (2) $66,667, (3) $63,246, (4) $60,571, (5) $58,566, (6) $57,083, (7) $55,978, (8) $55, 143, (9) $54,499, and (10) $53,991.

Finally, each study participant's revealed risk preference was assessed by a question adapted from Barsky et al. (1997). The question first asked:

> "Suppose you are the only income earner in the family, but that your current job is ending. You have to choose between two new jobs. The first job would guarantee your current family income for life. The second job is also guaranteed for life and possibly better paying, but the income is less certain. There is a 50-50 chance that the second job will double your

current family income for life and a 50-50 chance that it will cut your current family income by a third for life. Which would you take?"

This was followed by one of two questions based on each participant's original choice:

(a) "Now suppose the chances were 50-50 that the second job would double your current family income and 50-50 that it would cut it in half. Would take the job?" or

(b) "Now suppose that chances were 50-50 that the second job would double your current family income and 50-50 that it would only cut it by 20 percent. Would you take the job?"

An ordinal score ranging from 1 = *low risk tolerance* (high risk aversion) to 4 = *high risk tolerance* (low risk aversion) was estimated based on answers to these questions.

Data Analysis Methods

EEG data were processed offline using EEGLAB version 2019.1 through MATLAB (Delorme & Makeig, 2004). As shown in Figure 2.4, EEG data were recorded digitally as a time series or as a continuous flow of voltages.

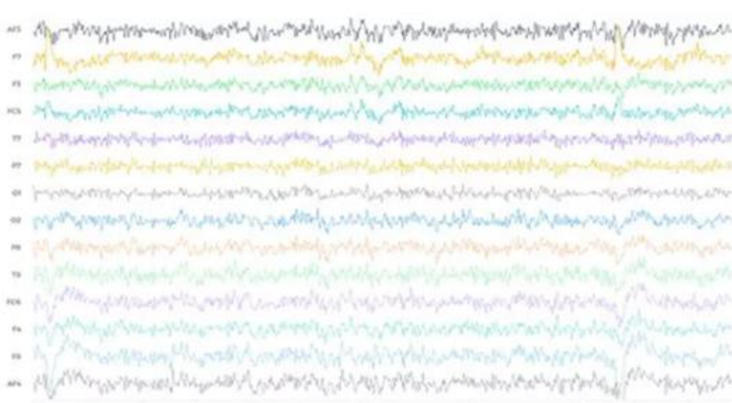


Figure 2.4. EEG Wave Record Time Domain (*Note*. Illustration adapted from Emotiv, 2022 (https://www.emotiv.com). In the public domain*)*.

Before analyzing participant data, measurement artifacts were identified and removed. Cleaning of data is important because EEG signals are susceptible to bodily changes (e.g., sudden movements and physiological disturbances such as eye movements, eye blinking, and muscular activity). These artifacts must be removed to ensure that the EEG signals are not contaminated (Roy et al., 2021). In this regard, EEG signals contain two different categories of artifacts, which are extrinsic and intrinsic artifacts (Kotte & Dabbakuti, 2020). Extrinsic artifacts mostly come from external factors (e.g., environmental noise and body movements) or movements in the EEG device, whereas intrinsic artifacts come from the body's physiological activities (Uriguen & Garcia-Zapirain, 2015). To remove extrinsic artifacts signal, the data in each channel was bandpass filtered from 0.5 to 65 Hz (Christiano & Fitzgerald, 2003). Intrinsic artifacts were removed by the Independent Component Analysis (ICA) method embedded in EEGLAB. ICA is widely used in EEG research to remove artifacts in EEG data by decomposing mixed-signal sources. Specifically, the Extended Informax ICA algorithm, as discussed below, was used for this study because of its reliability (Delorme et al., 2007; Jebelli et el., 2018; Lee et al., 1999; Viola et al., 2010).

Extended Informax ICA algorithm. Assume there is an *M*-dimensional zero-mean vector $s(t) = [s_1(t), \ldots, s_M(t)]^T$, such that the components $s_i(t)$ are mutually independent. The vector $s(t)$ corresponds to *M* independent scalar-valued source signals $s_i(t)$. The multivariate probability density function of the vector as the product of marginal independent distribution is

$$p(\mathrm{s}) = \prod_{i=1}^{M} p_i(s_i) \tag{2.5}$$

A data vector $x(t) = [x_1(\mathrm{t}), \ldots, x_N(\mathrm{t})]^T$ is observed at each time point *t*, such that

$$x(t) = \mathrm{As(t)} \tag{2.6}$$

$$u(t) = Wx(t) = WAs(t) \quad (2.7)$$

where u is the unmixed signals at each time point t, W is the linear mapping of a data vector $x(t)$, A is a full-rank N x M scalar matrix, and s is the sources from the mixed signals.

After removing artifacts, data were linked with the three elements of the study by participant: (a) the survey, (b) the choice dilemma, and (c) the risk-taking task. EEG features in the frequency domain were then extracted for each element. Alpha, beta, and gamma EEG waves were compared between those who elected to engage in the risk-taking task and those who did not engage in the task.

Results

Table 2.4 shows the results from the tests designed to address the first research question, which asked: Do measures of self-assessed financial risk-tolerance and other personal characteristics correlate with engagement in risk-taking behavior? Given the size of the sample, median, Median Absolute Deviation (*MAD*), and Mann-Whitney U tests were used to evaluate this question. Four variables were found to be associated with risk-taking. Study participants who reported higher levels of subjective financial knowledge and financial experience were more likely to make the wager. It is possible that given the complexity of estimating odds associated with the risk-taking task, those with greater financial knowledge and experience were able to conceptualize the activity in a way that reduced the stress associated with the choice dilemma. Answers to the SCF risk-assessment item and the measure of CRRA were also found to be associated with engagement in the risk-taking task. Those who indicated a greater willingness to take risk (i.e., they were less risk averse) were observed to be more likely to engage in the wager.

Table 2.4. Risk Tolerance and Personal Characteristics Associated with Engaging in Risk-Taking Task

Variable	*Mdn*	*MAD*	RTT: No *Mdn* (*MAD*)	RTT: Yes *Mdn* (*MAD*)	*p* [a]
Mood	8.00	1.35	8.86 (1.22)	7.33 (1.16)	n.s.
Willingness to Gamble	2.00	0.92	2.14 (1.07)	2.33 (0.58)	n.s.
Willingness to Bet	1.00	1.06	1.57 (1.13)	2.00 (1.00)	n.s.
Financial Satisfaction	5.50	1.65	5.14 (1.58)	6.00 (2.00)	n.s.
Financial Knowledge	6.00	2.04	5.29 (1.60)	8.33 (1.16)	< .05
Knowledge of Games	2.50	2.31	3.71 (2.69)	2.33 (0.58)	n.s.
Financial Experience	7.00	2.30	5.86 (2.04)	9.00 (1.00)	< .05
Self-Assessed Risk Tolerance	4.50	2.22	4.00 (2.31)	5.33 (2.08)	n.s.
SCF Risk Measure	2.00	0.79	1.86 (0.69)	3.00 (0.00)	< .05
Financial Risk Tolerance	23.00	3.69	22.00 (3.06)	26.67 (3.22)	n.s.
Constant Relative Risk Aversion	6.50	3.31	7.57 (2.15)	2.00 (1.73)	< .05
Revealed Risk Preference	2.00	1.07	2.57 (1.13)	2.67 (1.16)	n.s.

Note. n.s. = not significant; [a]Mann-Whitney U Test; RTT = Risk-Taking Task.

Table 2.5 shows the mean power band scores by study participant across the three brain waves by each element of the study (i.e., survey, choice dilemma, and risk-taking task). The fifth, eighth, and eleventh columns show the average power band wave size by participant. These data were used in the comparison tests to answer the question that asked, “Can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in a financial risk-taking activity?”

Table 2.5. Mean Power Band Alpha, Beta, and Gamma Brain Wave Values by Node

Study Participant	Stage	Alpha		Avg	Beta		Avg	Gamma		Avg
		P7	P8		FC5	FC6		T7	T8	
PP 1 RTT: Yes	Survey	41.61	37.66	39.64	38.09	39.05	38.57	23.61	26.74	25.18
	CD	48.00	42.78	45.39	39.12	40.70	39.91	26.73	27.38	27.06
	RTT	44.02	40.65	42.34	38.04	43.31	40.68	23.74	30.94	27.34
PP 2 RTT: No	Survey	41.17	39.33	40.25	35.78	35.45	35.62	22.95	30.82	26.89
	CD	41.94	28.55	35.25	39.37	41.20	40.29	34.25	46.05	40.15
	RTT	45.25	30.49	37.87	42.02	40.59	41.31	36.01	36.41	36.21
PP 3 RTT: Yes	Survey	40.87	38.69	39.78	35.26	36.93	36.10	20.81	28.68	24.75
	CD	42.75	42.11	42.43	26.89	38.90	32.90	30.73	38.31	34.52
	RTT	43.90	44.94	44.42	41.07	43.65	42.36	33.06	40.14	36.60

PP 4 RTT: Yes	Survey	40.46	38.35	39.41	33.73	35.88	34.81	20.14	18.78	19.46
	CD	46.83	43.67	45.25	38.33	39.85	39.09	26.75	26.96	26.86
	RTT	42.20	41.17	41.69	36.72	38.38	37.55	24.49	25.30	24.90
PP 5 RTT: No	Survey	45.80	41.90	43.85	38.38	39.15	38.77	25.00	24.97	24.99
	CD	53.87	53.18	53.53	47.57	48.11	47.84	32.93	32.69	32.81
	RTT	56.22	52.67	54.45	46.71	47.70	47.21	34.35	34.86	34.61
PP 6 RTT: No	Survey	39.51	39.20	39.36	32.66	34.83	33.75	20.48	20.03	20.26
	CD	40.70	37.60	39.15	33.71	36.59	35.15	23.20	24.09	23.65
	RTT	39.33	35.86	37.60	36.22	37.87	37.05	23.89	27.61	25.75
PP 7 RTT: No	Survey	43.59	41.71	42.65	35.28	38.26	36.77	24.92	23.27	24.10
	CD	48.92	43.67	46.30	41.52	48.67	45.10	35.99	39.44	37.72
	RTT	45.97	41.17	43.57	45.31	46.89	46.10	43.88	41.64	42.76
PP 8 RTT: No	Survey	35.69	39.22	37.46	34.23	39.22	36.73	21.50	23.89	22.70
	CD	42.43	39.17	40.80	36.87	42.13	39.50	26.62	30.12	28.37
	RTT	41.48	38.84	40.16	40.24	44.30	42.27	27.13	32.33	29.73
PP 9 RTT: No	Survey	39.20	37.64	38.42	32.20	36.69	34.45	22.64	22.12	22.38
	CD	42.61	39.63	41.12	33.86	38.21	36.04	26.55	31.40	28.98
	RTT	42.03	41.70	41.87	33.06	35.04	34.05	22.69	30.23	26.46
PP 10 RTT: No	Survey	44.84	43.23	44.04	34.55	36.34	35.45	19.62	21.46	20.54
	CD	46.12	45.09	45.61	36.98	40.37	38.68	27.05	20.83	23.94
	RTT	44.78	44.17	44.48	33.90	40.32	37.11	27.76	29.17	28.47

Note. CD = Choice Dilemma; PP = Participant; RTT = Risk-Taking Task.

Table 2.6 shows the same data by group (i.e., those who engaged in the risk-taking task and those who did not).

Table 2.6. Mean Power Band Alpha, Beta, and Gamma Brain Wave Values by Group and Node

Group	Stage	Alpha		Avg	Beta		Avg	Gamma		Avg
		P7	P8		FC5	FC6		T7	T8	
RTT: Yes	Survey	40.98	38.23	39.61	35.69	37.29	36.49	21.52	24.73	23.13
	CD	45.86	42.85	44.36	34.78	39.82	37.30	28.07	30.88	29.48
	RTT	43.37	42.25	42.81	38.61	41.78	40.20	27.10	32.13	29.61
RTT: No	Survey	41.40	40.32	40.86	34.73	37.13	35.93	24.44	23.79	23.12
	CD	45.23	40.98	43.11	38.55	42.18	40.37	29.51	32.09	30.80
	RTT	45.01	40.70	42.85	39.64	41.82	40.73	30.82	33.18	32.00

Note. CD = Choice Dilemma; RTT = Risk-Taking Task.

Whereas data in Table 2.5 and 2.6 show power band data by study participant and node, data in Table 2.7 show average alpha, beta, and gamma brain wave data across the three elements of the study. Differences between those who engaged in the risk-taking task and those who did not was assessed with *t* tests. Only one significant difference was observed: Those who engaged in the risk-taking task(s) exhibited lower beta wave activation during the choice dilemma phase of the study. Although the risk takers almost uniformly exhibited less brain activation, none of the other comparisons were statistically significant.

Table 2.7. Statistical Significance in Power Band Wave Values

	Alpha			Beta			Gamma		
Risk-Taking Task Group	Survey	Choice Dilemma	Risk-Taking Task	Survey	Choice Dilemma	Risk-Taking Task	Survey	Choice Dilemma	Risk-Taking Task
No	40.86	43.11	42.85	35.93	40.37	40.73	23.12	30.80	32.00
Yes	39.61	44.36	42.81	36.49	37.30	40.20	23.13	29.48	29.61
p	.104	.406	.959	.100	.001	.449	.996	.431	.140
Number of Observations	50			170			340		

Note. The number of observations was estimated as the total number of values within the frequency range of each wave (i.e., Alpha: 5Hz, Beta:17 Hz, and Gamma: 34 Hz) for each participant.

When viewed collectively, the results from Table 2.4 and Table 2.7 offer tantalizing insights into the risk-taking decision-making process. Recall from Table 2.4 that greater financial knowledge, more financial experience, higher risk tolerance, and less financial aversion were associated with engagement in the risk-taking task. The results present the possibility that rather than being a neural activity, risk-taking may be primarily a trait or characteristic factor. According to this line of thinking, knowledge, experience, and risk tolerance create a personal framework in which someone is predisposed to engage in a risk-taking activity. It follows then that any brain activation observed in relation to risk-taking tasks is an artifact that follows trait and personal characteristics. If true, then differences in alpha, beta, and gamma brain waves should be observed between those with low and high degrees of financial knowledge, experience, and risk tolerance/aversion. Tests were undertaken to examine this possibility. Participant data were segmented into financial knowledge, financial experience, risk tolerance (SCF Risk Measure), and risk aversion (CRRA) categories based on a variable median split. Alpha, beta, and gamma waves, across the three elements of the study (i.e., survey, choice dilemma, and risk-taking task), were examined with *t* tests.

Table 2.8 shows these results. Significant differences existed in more than half of the comparisons. Those with high self-assessed financial knowledge exhibited lower alpha wave activation during the survey and risk-taking task, lower beta wave activation during the choice dilemma, and lower gamma wave activation during the choice dilemma and risk-taking task. Those with more financial experience had lower alpha wave activation during the survey and lower beta wave and gamma wave activation during the choice dilemma and risk-taking task. A similar pattern of brain activation was observed in relation to risk tolerance. Differences based on risk aversion were also observed. Those with low-risk aversion had lower alpha wave activation during the survey, choice dilemma, and risk-taking task. Those with low-risk aversion also had lower beta wave activation during the choice dilemma.

Table 2.8. Power Band Alpha, Beta, and Gamma Brain Wave Values by Knowledge, Experience, Risk Tolerance, and Risk Aversion

	Financial Knowledge			Financial Experience			Risk Tolerance			Risk Aversion		
Stage	Low	High	*p*	Low	High	*p*	Low	High	*p*	Low	High	*p*
Alpha												
Survey	41.84	39.13	.001	41.11	39.55	.028	41.11	39.55	.028	39.31	41.66	.001
Choice Dilemma	44.35	42.61	.204	43.76	43.06	.618	43.76	43.06	.618	41.83	45.14	.014
Risk-Taking Task	44.43	41.30	.015	43.72	41.58	.111	43.72	41.58	.111	41.29	44.44	.015
Beta												
Survey	36.21	35.99	.481	36.30	35.81	.124	36.30	35.81	.124	36.37	35.84	.091
Choice Dilemma	41.58	37.29	.001	41.23	36.75	.001	41.23	36.75	.001	38.33	40.54	.001
Risk-Taking Task	41.16	39.98	.068	41.34	39.41	.003	41.34	39.41	.003	40.83	40.31	.413
Gamma												
Survey	23.78	22.47	.321	23.60	22.41	.378	23.60	22.41	.378	23.80	22.45	.309
Choice Dilemma	32.65	28.05	.001	31.94	27.97	.007	31.94	27.97	.007	31.39	29.31	.149
Risk-Taking Task	33.70	28.86	.001	33.04	28.65	.004	33.04	28.65	.004	30.96	31.61	.660

Although preliminary, findings from this study suggest that engagement in risk-taking tasks is not primarily associated with alpha, beta, or gamma brain wave activation. Brain wave activation, and the resulting engagement in a risk-taking task, appears to be associated most directly with levels of financial knowledge, financial experience, risk tolerance, and risk aversion. These factors may act in a way that primes someone to take risk. It is noteworthy, however, that those who engaged in the risk-taking task exhibited less alpha, beta, and gamma brain wave activation.

Discussion and Implications

The following questions were asked at the outset of this study: (a) do measures of self-assessed financial risk-tolerance and other personal characteristics correlate with the engagement in risk-taking behavior and (b) can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in a financial risk-taking activity? In relation to the first question, results indicated that, among those in the sample, subjectively assessed financial knowledge, financial experience, and risk tolerance/aversion were associated with engaging in the risk-taking task. Those with more knowledge and experience were more likely to take the offered risk. As expected, those with more risk tolerance (less risk aversion) were also more likely to engage in the risk-taking task. These findings support previous risk-tolerance and risk-taking literature (Blais & Weber, 2006; Fisher & Yao, 2017; Grable et al., 2020).

Findings from this study are noteworthy in expanding the risk-tolerance and risk-taking literature beyond the use of personal characteristics and attitudinal factors in describing risk-taking behavior. For example, those who were more attentive, focused, and cognitively engaged were less likely to engage in the risk-taking task. However, brain wave activation was generally not associated directly with making a wager.

Risk takers, at least in the context of the type of wager used in this study, appear to be less engaged, focused, and thoughtful compared to those who are more risk averse. Risk takers also appear to be more relaxed during periods leading up to a risk-taking opportunity. Rather than being triggered by the activation of brain waves, the choice to take a risk or not take a risk appears to be described more completely by someone's financial knowledge, experience, and willingness to take risk. These factors appear to make someone predisposed to taking a risk. This does not mean, however, that a risk-taker is not physiologically aroused before or during a risk-taking activity. Instead, this means, in response to the second research question, that risk-taking is not reliant on the activation of alpha, beta, or gamma waves.

Findings from this study provide support for the notion that risk is an important factor in describing risk-taking activity. At the outset, it is important to acknowledge that it is possible for a risk seeker and risk avoider to engage in a similar risk-taking task. It is also possible for a risk seeker and risk avoider to avoid risk-taking behavior. The difference between a risk seeker and a risk avoider may be that a willingness to take risk—based on knowledge and experience and an innate tolerance for risk—primes a person to be more likely to engage in a risk-taking activity. Rather than prompting brain activation, risk seekers appear to react with less cognitive effort. Data from this study suggest that a risk seeker does not necessarily need to be cognitively engaged in the risk-taking decision process. Risk avoidance behavior appears to be associated with elevated levels of brain activation, particularly among those with lower levels of financial knowledge, financial experience, and risk tolerance. In order to prompt a risk avoider to take a risk it may be necessary to reduce stimuli and moderate the brain response. This could be achieved by providing mindfulness mediation practices or managing distractions during the decision-making process.

These insights have implications for those who are in the financial services and gaming industries. Consider again the scenario presented in the introduction to this paper. Two otherwise similar people were described as walking into an investment advisor's office. The two individuals, like the participants in this study, shared common demographic and socioeconomic characteristics. Both entered the financial advisor's office with a monetary endowment. It was then asked which of these two would be more likely to make a risky investment or savings choice or to engage in a wager in which the outcome is uncertain and potentially negative? It turns out that the person with more financial knowledge, more financial experience, and a higher tolerance for risk is more apt to take the financial risk. Results from this study also suggest that the risk taker will likely be the one who is less cognitively engaged and less emotionally focused on the choice dilemma. It is important to note that rather than presenting anxiety, fear, or stress, the risk takers in this study initially exhibited relaxation and calmness, even when the situation was potentially stressful (i.e., wearing a scalp assessment device while taking a survey). This result indicates a strategy when presenting risky choices to individuals: Make the risk-taking choice environment as enjoyable and relaxing as possible.

Limitations

The results from this study, while providing unique insights into the way brain activation is associated with financial risk-taking, have generated as many or more questions than the questions answered. For example, future studies are needed, using larger samples, to determine if the way a risk-taking question is framed may trigger different alpha, beta, and gamma brain wave responses. In this study, the risk-taking task was framed neutrally. It is possible, as described in prospect theory (Kahneman, 2011; Kahneman & Tversky, 1979; Tversky & Kahneman, 1992), that framing the risk-taking task either positively or negatively might activate different alpha, beta, and gamma responses. Additionally, the dollar amount at risk may be related to the choice to engage in a risk-taking behavior. It is possible that the $25 endowment used in this study was not enough to warrant someone’s time to engage in the last step of the study. It is also possible that the endowment was considered too valuable to lose. Future studies, using different dollar endowments, are needed to explore this issue. In addition, the activity itself may trigger different brain activation. It may be that a gambling scenario activates different brain regions compared to investment or saving scenarios. Finally, although prescreening and a general comparison of brain waves were conducted across the participants, differences in cognitive ability (i.e., Attention-Deficit/Hyperactivity Disorder, etc.) were not evaluated before, during, or after the experiment. The potentiality that medically diagnosed cognitive conditions could be related to brain wave activity in the context of risk-taking behavior is worthy of future study.

When viewed holistically, the results from this study are noteworthy in showing that brain wave activation is not directly associated with the choice to engage in a financial risk-taking task. Brain wave activation in relation to financial risk taking is more directly related to someone’s level of financial knowledge, financial experience, and willingness to take risk. The use of EEG methodologies, as a clinical and research tool, as exemplified by this study, shows great promise in providing more insights into how individuals conceptualize and act when faced with financial choices that entail the possibility of uncertain gains and losses.

CHAPTER 3

THE ROLE OF RISK TOLERANCE AS A MEDIATOR BETWEEN HOUSEHOLD INCOME AND TOBACCO AND ALCOHOL USE AMONG MID-LIFE ADULTS IN THE UNITED STATES

Introduction

According to the Centers for Disease Control and Prevention (CDC; 2021), every six in ten adults exhibit symptoms of chronic disease. These diseases are the leading causes of death and disability in the United States. Tobacco and alcohol use are known lifestyle risks that have been linked with chronic disease in the United States (CDC, 2021). Numerous studies have addressed the relationship between socioeconomic status (SES) (i.e., poverty level, educational attainment, and employment status) and tobacco and alcohol use (e.g., O'Neill, 2005; Pampel & Rogers, 2004; Pollack et al., 2007). Results from such studies suggest that those living below the poverty line tend to exhibit higher rates of tobacco use. In contrast, those living above the poverty level generally consume more alcohol.

While the association among tobacco and alcohol use, problematic health outcomes, and the socioeconomic situation is well established in the literature (see Mokdad et al., 2004; Sturm, 2002), less is known about the association between health-related sensation-seeking behavior, of which tobacco and alcohol use are sensation-seeking proxies, and factors related to financial well-being, which is generally conceptualized as a person's perception of being able to maintain a current, an anticipated, and a desired standard of living (Brüggen et al., 2017). These relationships are important (see Zinn, 2019). What is generally known is that the monetary costs associated with using tobacco and alcohol can dramatically reduce resources available to fund saving and investment needs at the household level, especially for those at lower-income levels (O'Neill et al., 2005; Walsh et al., 2013). It is also known that sensation-seeking behavior inflicts more harm among socioeconomically disadvantaged households (Pampel & Rogers, 2004). When viewed this way, expenditures on tobacco and alcohol may be a primary force reducing a household's cash flow position, thus reducing net worth gains, primarily because the engagement in problematic health-related sensation-seeking activities substitutes for saving and investing (O'Neill, 2009). Additionally, because of the association between tobacco and alcohol use and chronic disease (i.e., tobacco and alcohol use behavior are factors associated with chronic health conditions), health care costs tend to be higher for those who use tobacco and more than modest amounts of alcohol on a regular basis (CDC, 2021).

Statement of Purpose

The goal of this study was to estimate the association between household income and tobacco and alcohol use. Additionally, this study aimed to measure the mediation effect of risk tolerance—as measured across seven domains (i.e., driving, financial matters, occupational, health, faith in people, romantic relationships, and major life change)—in describing tobacco and alcohol use.[8] Findings from this study provide insight into the health-socioeconomic effect by suggesting that there may be ways health and personal finance researchers, educators, and policymakers can

[8] While a moderation analysis seeks to examine how the relationship between two variables (i.e., household income and tobacco and alcohol use) changes depending on the level of the third variable (i.e., risk tolerance in this study), the purpose of the current study is to gain a better understanding of the causal link between household income and tobacco and alcohol use, and identify a mediator variable (risk tolerance) that can explain the underlying mechanisms of the two variables (i.e., household income and tobacco and alcohol use) using both direct and indirect ways (via a mediation analysis).

work together to reduce problematic tobacco and alcohol use, via risk-tolerance education, as a tool to promote gains in household-level socioeconomic status.

Literature Review

Health, Socioeconomic Status, and Sensation-Seeking

In the literature, health status and socioeconomic status (SES) is associated (O'Neill, 2009; Rosen & Wu, 2004). While numerous indicators represent SES, household income is a popular gauge of SES and economic security. As noted by Pollack et al. (2007), higher SES tends to be positively related to increased longevity, higher self-ratings of health, improved functional status, and a decrease in chronic disease. Higher SES is also related to improved well-being and mental health (Bogan & Fertig, 2013), with SES acting as a buffer between health and financial shocks and economic security (Smith et al., 2005).

In order to better understand the relationship between SES and problematic health behavior, it is necessary to have a clear understanding of the term sensation-seeking. Sensation-seeking describes a person's preference for pursuing immediate pleasure in comparison to future satisfaction (Zuckerman, 1979). Sensation-seeking encompasses three domains: physical, social, and health. Horvath and Zuckerman (1993) defined tobacco use (i.e., smoking) and alcohol use (i.e., drinking) as two forms of health sensation-seeking behavior. When viewed as sensation-seeking behavior, tobacco and alcohol use are known to be related to household income levels (Auld, 2005; Blakely et al., 2005). No consensus on the causal mechanism linking tobacco and alcohol use to SES (Wei et al., 2020) has been established. What is known is that smokers tend to come from lower-income households, while those who spend more money on alcohol on a regular basis come from higher-income households (Collins, 2016; Hiscock et al., 2012).

The pathways linking SES to better health outcomes stems from the notion that increased income allows a household to live in high-quality housing, have access to better education, and gain access to more and better health (and financial) information and care (Marmot, 2002). The relationship between SES and better life outcomes fits well with the concepts embedded in social vulnerability theory (Ross &Wu, 1995). As noted by Pampel and Rogers (2004), those who exhibit high SES:

> Develop greater resistance to disease because they enjoy better medical care, nutrition, and comfortable living conditions while growing up. These resources contribute over time to greater physiological resilience in dealing with the harm of lifestyles such as smoking. By contrast, because they have fewer resources for medical care, diet, and living conditions, members of lower socioeconomic status groups face more assaults on health over the life course that can decrease the body's resilience and ability to resist disease or, once ill, to recover from it" (pp. 308-309).

The tendency among low SES households to spend excessive amounts on sensation-seeking activities (based on a percent of available household resources) may result from a lack of information and counseling, as well as reduced access to healthy eating and recreational options. This pattern of behavior can be a symptom of insufficient resources to obtain quality care and behavioral alternatives (Bartley, 2019; Porter, 2019). This recurring pattern of behavior may limit a household's ability to improve SES outcomes in the long term (Pampel et al., 2010).

While much of the extant literature shows a direct relationship between SES and engagement in health-related sensation-seeking behavior, a possible association may be indirectly explained. As O'Neill (2009) pointed out, allocating household resources to activities that increase the probability of ill health means more household income will be spent on medical expenses. This excessive spending, in turn, can increase financial and psychological strain, leading to barriers to achieving gains in SES. This points to a possible mediated effect between health status and SES. As physical health deteriorates, so does earnings potential. Stated another way, chronic health conditions can limit job productivity (Zagorsky, 2005), which can dampen SES.

Although consensus is lacking regarding causality, almost all theories and models used to evaluate the relationship between SES and health-related sensation-seeking behavior suggest that SES, or factors comprising SES, plays a critical role in describing a person's choice to engage in problematic behavior (Zuckerman, 1983). At a minimum, the relationship may be an indirect one through another variable, such as risk tolerance. The current study examined this possibility.

Risk Tolerance

Risk tolerance is defined as a person's willingness to take risks when deciding whether the outcomes are both unknown and potentially negative (Grable, 2000). Risk tolerance is important in understanding and interpreting household saving, spending, and investing behavior (Gutter et al., 2012; Lee & Kim, 2017). Evaluating risk tolerance is a cognitive task that requires someone to respond to one or more scenarios using subjective estimates of outcome probability. Those who perceive risks as potentially harmful or costly tend to exhibit low-risk tolerance (i.e., high-risk aversion) and vice versa.

It is possible that risk tolerance,[9] across domains, may play an important role in describing health-related behavioral choices. However, it is interesting to note that this potential relationship, between risk tolerance and health-related behavior choices, has not been widely studied by health researchers. Some evidence exists that different domains of risk tolerance are associated with what

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[9] Closely related to the concept of risk tolerance is the notion of risk perception. Risk perception is defined as a decision-maker's subjective judgment about the likelihood of a negative occurrence or decision outcome (Paek and Hove, 2017). Yan and Brocksen (2013) showed that high risk perception—a construct akin to high risk aversion—lowers the likelihood of substance abuse.

Irwin and Millstein (1986) and Grable and Joo (2004) labeled environmental and personal biopsychosocial characteristics. The literature is replete with examples of how household income, and to some extent sensation-seeking preferences, are related to a person’s willingness to take a risk. The consensus within the literature is that high personal and household income acts as a marker of increased tolerance for financial risk. In contrast, a preference for engagement in sensation-seeking activities acts as a proxy for risk-taking in the health domain. Conceptually, household income is generally considered an antecedent or predisposing household situational factor that directly describes a person’s degree of risk tolerance (Pinjisakikool, 2017; Wong, 2011; Wright, 2017). The reason is that income is considered an indicator of household financial capacity (Cordell, 2002). Households with greater financial capacity are generally better able to deal with losses associated with unexpected financial, lifestyle, and health losses, and as such, researchers generally assume that income is a determinant of risk tolerance rather than risk tolerance shaping income (Fisher &Yao, 2017; Hanna et al., 2008).

The domains of risk tolerance are ethical, financial, health/safety, social, and recreational situations (Weber et al., 2002). While researchers continue to debate the degree to which the domains of risk tolerance are correlated, the general consensus is that individuals who are willing to take risks in one domain should be willing to engage in behavior in other risk-tolerance domains (Hanoch et al., 2006; Szrek et al., 2012). Of importance to note is that measures and domains of risk tolerance are not interchangeable (Grable & Rabbani, 2014). The relationship one domain of risk tolerance has with an outcome of interest will differ based on the social context of the situation and a person’s unique circumstances. For example, someone who exhibits high health risk tolerance (i.e., they are willing to engage in what are generally unhealthy behaviors) may be more prone to use tobacco and consume alcohol to excess. However, this same person may not be willing to invest their money aggressively or take social risks.

Conceptual Model and Research Questions

In this study, sensation-seeking behavior was proxied by tobacco and alcohol use among *current* tobacco and *current* alcohol users. As previously noted, the literature shows clear associations between and among household income, tobacco (Grafova, 2011) and alcohol (Auld, 2005) use, and risk tolerance (Pampel & Rogers, 2004; Ross & Wu, 1995). Additionally, an association between income (both personal and household) and risk tolerance has been documented in the literature (Wong, 2011; Wright, 2017). The literature is relatively silent, however, in describing the possible mediating effects of risk tolerance on sensation-seeking behavior. It may be possible that risk tolerance—as an indicator of a cognitive appraisal—plays a key role in describing the level of tobacco and alcohol use among current users of tobacco and alcohol. If this is the case, risk-tolerance education may provide a pathway to helping, both directly and indirectly, mitigate harmful tobacco and alcohol use.

This study was guided by a biopsychosocial model of risk-taking behavior proposed by Irwin and Millstein (1986) and the concept of social vulnerability (Ross & Wu, 1995). The model shown in Figure 3.1 illustrates the conceptualization of the study. Factors thought to increase the probability that a person will engage in risk-taking behavior are classified as (a) predisposing endogenous and predisposing exogenous factors and (b) precipitating factors. Irwin and Millstein (1986) noted that characteristics such as age, gender, and racial/ethnic background are examples of predisposing endogenous factors (i.e., characteristics unique to an individual), while income is a predisposing exogenous factor (i.e., a behavior influence arising outside of the individual). They also showed that psychological and social/environmental variables (i.e., cognitive scope, perceptions of the society/environment, personal values, etc.) function as precipitating behavior factors (e.g., triggers of behavior). When viewed this way, risk tolerance can be viewed as a precipitating psychological factor (or trait) that proceeds the engagement in risk-taking behavior. The predisposing endogenous and exogenous factors in the model tend to be correlated.

Figure 3.1. The Biopsychosocial Causal Model of Risk-Taking Behavior (Irwin & Millstein, 1986; Ross & Wu, 1995)

Based on the pathway presented in the model, the following research questions were tested:

RQ$_1$: The relationship between household income (i.e., predisposing exogenous factor) and tobacco use (i.e., risk-taking behavior) is negative.

RQ$_2$: The relationship between household income (i.e., predisposing exogenous factor) and alcohol use (i.e., risk-taking behavior) is positive.

RQ$_3$: The relationship between household income (i.e., predisposing exogenous factor) and tobacco use (i.e., risk-taking behavior) is mediated by risk tolerance (i.e., precipitating factor in seven domains: driving, financial matters, occupation, health, faith in people, romantic relationships, and major life change).

RQ$_4$: The relationship between household income (i.e., predisposing exogenous factor) and alcohol use (i.e., risk-taking behavior) is mediated by risk tolerance (i.e., precipitating factor in seven domains: driving, financial matters, occupation, health, faith in people, romantic relationships, and major life change).

Methods

Data

Data for this study were obtained from the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 is a survey sponsored by the U.S. Bureau of Labor Statistics, and it is a nationally representative survey. The NLSY79 is a cohort born in the U.S. between 1957 and 1964, and the survey was started in 1979 when participants were 14 to 22 years of age. The same individuals have been and continue to be surveyed, and study participants are interviewed on a biennial basis. The NLSY79 survey was created to study the transition from school to work and careers among adolescents and young adults in the late 1970s (Rothstein et al., 2019). The cross-sectional 2012 wave of data was used for this study. Although another wave of the survey, conducted in 2014, included a question related to one of the main variables of interest, the number of responses was too low (approximately one-third fewer compared to the second-to-last survey conducted in 2012) to provide meaningful analytic insights. In 2012, those in the sample were aged 54 to 62 as mid-life adults who were at substantial risk of misusing alcohol and tobacco (Blow & Barry, 2012). The sample was delimited to include only *current* smokers and users of alcohol, and these two categories were not mutually exclusive. The analytic sample size included 1,377 *current* smokers and 3,964 *current* alcohol users (i.e., drinkers). Data were weighted to represent the U.S. population as of 2012 using sample weight values provided by the U.S. Bureau of Labor Statistics.

Variables

In the models, the primary independent variable of interest was total net household income. Household income was assessed by combining all income sources in a household (e.g., wages, unemployment compensation, net business income, net farm income, child support, alimony, Supplemental Security Income, disability benefit, unemployment compensation, etc.). The resulting dollar amount was log-transformed. The dependent variables were tobacco and alcohol use. Tobacco use was estimated by asking *current* smokers the number of cigarettes smoked per day (i.e., "How many cigarettes do you smoke per day?"). The alcohol use variable was estimated by asking *current* drinkers the number of days they consumed alcohol in the last 30 days (i.e., "During the last 30 days, on how many days did you drink any alcoholic beverages, including beer, wine, or liquor?").[10]

Seven domain-specific risk-tolerance variables were used as mediating variables in the models. The following risk tolerance question asked across the domains in the NLSY79: "People can behave differently in different situations. How would you rate your willingness to take risks in the following areas? For each situation, rate your willingness from 0 to 10, where 0 means *unwilling to take any risks* and 10 means f*ully prepared to take risks*. The seven areas were: (a) driving, (b) financial matters, (c) occupation, (d) health, (e) faith in people, (f) romantic relationships, and (g) major life change.[11] It is important to note that the survey does not provide specific examples of what should or could be included in each domain.

The following control variables, which align with the conceptual model of risk-taking behavior shown in Figure 3.1, were included in the analyses: age, gender, racial/ethnic background, education, employment status, and marital status. The choice of these variables was based on a review of the most common control variables used in the SES-health literature (see O'Neill et al., 2005; Pampel & Rogers, 2004; Rosen & Wu, 2004). Age was measured in years. Gender was dummy coded so that males were coded 1 and females 0. Given the way racial/ethnic background

[10] The reference numbers of the questions in the NLSY survey were T3976000 for tobacco use and T3976300 for alcohol use.
[11] The validity and statistical robustness of the items was assessed by Grable and Rabbani (2014). They noted that the items correlate positively but that each item represents a separate domain of risk tolerance, and as such, one item cannot be used as a proxy for another. As such, in this study, each of the seven variables will be tested in the models.

was measured in the NLSY79, three racial/ethnic variables were used. Those who self-identified as *Black* were coded 1, otherwise 0 (i.e., Hispanic, Non-Black, and Non-Hispanic). In a similar way, self-identified Hispanics were coded 1, otherwise 0 (i.e., Black, Non-Black, and Non-Hispanic). Those who self-identified as *Non-Black, Non-Hispanic* were coded 1, otherwise 0. This category or racial/ethnic background was used as the comparison group in the analyses. Education was also dummy coded. Those holding a *Bachelor's degree or higher level of education* was coded 1, whereas those with an *Associate's degree or less* was coded 0. Employment and marital status were coded dichotomously with those who were *currently employed* (i.e., working), and those who were *married* at the time of survey completion were coded, respectively, 1, otherwise 0.

Data Analyses

Several statistical tests were used to provide insights into the mediation effect of risk tolerance on the association between household income and tobacco and alcohol use. First, descriptive statistics were analyzed to portray the sample used in the study. To identify the relationship between household income, control variables, and tobacco and alcohol use, a series of ordinary least squares (OLS) regression analyses were estimated. A four-step approach described by Baron and Kenny (1986) was used (see James & Brett, 1984; Judd & Kenny, 1981) to test the mediation effect when risk tolerance is included as a mediator in the model. Figure 3.2 provides a conceptual illustration of the mediation effect model that was assessed in this study. To evaluate the significance of the mediation effect, a Sobel test (i.e., a *z*-score test; see Baron & Kenny, 1986; Coquelet et al., 2019; Moyer & Song, 2019; Perry & Morris, 2005; Sobel, 1982, 1986) was additionally undertaken. The Sobel tests provide an approximate estimate of the standard error of the mediation effect to ensure that the mediation effect on the relationship between the independent variables and the dependent variables are significantly different from zero at the alpha level of

0.05 or less. Lastly, a path analysis and a sensitivity analysis for the casual mediation models were performed as a robustness check. These methodological techniques were used to ensure the robustness of the empirical findings (Imai et al., 2010; Tingley et al, 2014; Zhu et al., 2022). Path analysis is a statistical technique used to depict the influence of a set of variables on one another in cases where a causal relationship may exist (Stage et al., 2004). Sensitivity analysis provides evidence that the core mediation findings are robust to potential violations of the fundamental identifying assumption of the causal mediation model (Hong et al., 2018; Kenny, 2021; Imai et al., 2010; Rosenbaum, 2002).

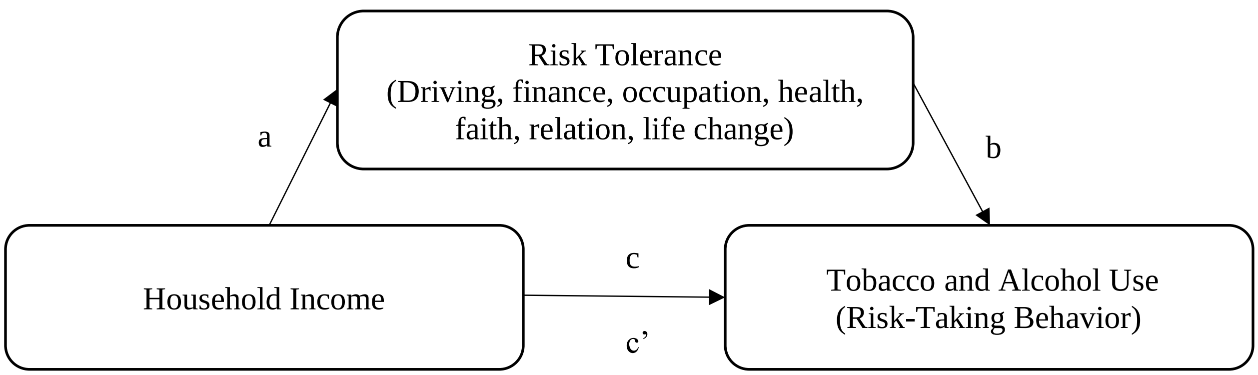

Figure 3.2. Conceptual Illustration of Risk Tolerance as a Mediator between Household Income and Tobacco and Alcohol Use *(Note.* a*b = Indirect/Mediation Effect; c = Total Effect; c’ = Direct Effect)

<u>Results</u>

Table 3.1 provides descriptive statistics for the variables used in this study. Study participants who used tobacco indicated smoking approximately 14 cigarettes per day on average. Those who indicated consuming alcohol reported drinking approximately eight days during the most recent month on average. Risk-tolerance scores were generally in the moderate to the moderately-low range, with driving and health risk-tolerance scores falling well below the average compared to the other risk-tolerance categories.

Table 3.1. Descriptive Statistics for Variables Used in the Study

Variable	Current Smokers (N_w= 6,470,862)	Current Drinkers (N_w= 36,012,422)
	Mean (*SD*)	
Smoking/Alcohol use	13.67(2.12)	8.21(1.07)
Household Income	42,614.09	92,154.02
Age	51.25 (2.22)	51.27 (2.21)
Risk Tolerance		
Driving	3.32 (1.38)	2.6 (3.28)
Finance	4.7 (3.55)	4.34 (2.97)
Occupation	5.56 (3.75)	5.10 (3.46)
Health	2.98 (3.67)	2.62 (3.08)
Faith	4.66 (3.43)	4.27 (2.96)
Relation	4.9 (4.23)	4.24 (3.62)
Life change	5.78 (3.53)	4.86 (3.05)
Variable	Percentage	
Gender		
Male	50.6	52.4
Female	49.3	47.7
Race		
Black	33.6	18.9
Hispanic	13.9	25.3
Others (Non-Black, Non-Hispanic)	52.5	55.8
Education Level		
Associate’s Degree or Less	84.3	60.2
Bachelor's Degree or Higher	15.7	39.8
Employment Status		
Working	56.8	79.3
Others (Laid off, looking for work, retired, others)	43.2	20.7
Marital Status		
Married	35.4	56.3
Others (Never married, others)	64.6	43.7

Note. N_w is a weighted sample size (Horvitz & Thompson, 1952; Lohr, 2021) using weight values provided by the U.S. Bureau of Labor Statistics.

Tables 3.2 and 3.3 show the results from the regression analyses. All coefficient values were statistically significant at the 0.001 level. Separate tests were conducted to estimate the level of multicollinearity in the data. The variance inflation factors ranged from 1.09 to 3.73 indicating little to modest multicollinearity in the models. When holding other factors constant, higher-income households were less likely to smoke than lower-income households across the seven risk-tolerance domains. For alcohol use, higher-income households were generally more likely to consume alcohol compared to lower-income households. Overall, these results were consistent with findings reported in the literature showing that tobacco users tend to come from lower-income households, whereas alcohol users generally come from higher-income households.

Risk tolerance across the seven domains was found to be positively related to tobacco and alcohol use, with the exception of faith, life change (for tobacco use), and driving (for alcohol use) risk tolerance. All the variables, except gender, exhibited the same directional (coefficient) relationship with tobacco use across the seven risk-taking domains controlling for other factors. Older, working, higher-household income study participants were less likely to smoke, whereas those who self-identified as Black or Hispanic, and those who were better educated and married, were more likely to smoke across each of the seven risk-tolerance domains. In the case of alcohol use, all the variables, except employment, also exhibited the same directional relationship across the seven domains of risk tolerance. Those who were older with higher-household income consumed more alcohol. Alternatively, those who self-identified as Black or Hispanic, were male, obtained a higher education level, and were married consumed less alcohol.

Table 3.2. OLS Regression Results Showing Variable Associations with the Tobacco Use

	Domains of Risk Tolerance						
	Driving *b (SE)*	Finance *b (SE)*	Occupation *b (SE)*	Health *b (SE)*	Faith *b (SE)*	Relationship *b (SE)*	Life Change *b (SE)*
Variable							
Age	-1.70 (0.00)	-1.50 (0.00)	-1.67 (0.00)	-1.59 (0.00)	-2.01 (0.00)	-2.23 (0.00)	-1.63 (0.00)
Gender	-0.24 (0.00)	0.68 (0.00)	0.02 (0.00)	0.65 (0.00)	0.16 (0.00)	-1.43 (0.00)	-0.28 (0.00)
Race (Black)	5.47 (0.00)	4.74 (0.00)	5.26 (0.00)	4.22 (0.00)	4.06 (0.00)	5.64 (0.00)	5.42 (0.00)
Race (Hispanic)	4.70 (0.00)	4.60 (0.00)	4.30 (0.00)	2.59 (0.00)	7.73 (0.00)	4.11 (0.00)	6.50 (0.00)
Education	7.72 (0.00)	6.45 (0.00)	7.18 (0.00)	6.98 (0.00)	11.17 (0.00)	9.75 (0.00)	7.65 (0.00)
Employment	-8.84 (0.00)	-9.71 (0.00)	-9.04 (0.00)	-9.65 (0.00)	-9.62 (0.00)	-8.93 (0.00)	-8.68 (0.00)
Marital Status	8.67 (0.00)	8.89 (0.00)	9.24 (0.00)	8.57 (0.00)	7.16 (0.00)	9.59 (0.00)	8.17 (0.00)
Household Income	-1.63 (0.00)	-2.29 (0.00)	-1.53 (0.00)	-3.63 (0.00)	-0.41 (0.00)	-1.21 (0.00)	-1.35 (0.00)
Risk Tolerance	0.04 (0.00)	0.28 (0.00)	0.27 (0.00)	0.57 (0.00)	-0.75 (0.00)	0.31 (0.00)	-0.12 (0.00)
Model							
Adj. R^2	.48	.47	.49	.53	.53	.50	.48
Constant	109.13	101.12	105.63	112.17	123.10	133.01	104.79

Note. All coefficients are significant at $p < 0.001$ level.

Table 3.3. OLS Regression Results Showing Variable Associations with the Alcohol Use

	Domains of Risk Tolerance						
	Driving *b (SE)*	Finance *b (SE)*	Occupation *b (SE)*	Health *b (SE)*	Faith *b (SE)*	Relationship *b (SE)*	Life Change *b (SE)*
Variable							
Age	0.64 (0.00)	0.64 (0.00)	0.64 (0.00)	0.64 (0.00)	0.66 (0.00)	0.61 (0.00)	0.64 (0.00)
Gender	-3.12 (0.00)	-2.94 (0.00)	-2.94 (0.00)	-2.64 (0.00)	-3.23 (0.00)	-2.44 (0.00)	-2.64 (0.00)
Race (Black)	-3.32 (0.00)	-3.40 (0.00)	-3.40 (0.00)	-3.23 (0.00)	-3.55 (0.00)	-4.13 (0.00)	-3.23 (0.00)
Race (Hispanic)	-4.20 (0.00)	-4.22 (0.00)	-4.22 (0.00)	-3.86 (0.00)	-4.32 (0.00)	-4.51 (0.00)	-3.86 (0.00)
Education	-1.79 (0.00)	-1.76 (0.00)	-1.76 (0.00)	-1.56 (0.00)	-1.36 (0.00)	-1.66 (0.00)	-1.56 (0.00)
Employment	-0.09 (0.00)	-0.37 (0.00)	-0.37 (0.00)	-0.36 (0.00)	-0.46 (0.00)	-0.86 (0.00)	-0.36 (0.00)
Marital Status	-1.78 (0.00)	-1.74 (0.00)	-1.74 (0.00)	-1.82 (0.00)	-1.38 (0.00)	-1.54 (0.00)	-1.82 (0.00)
Household Income	1.32 (0.00)	1.44 (0.00)	1.44 (0.00)	1.42 (0.00)	1.43 (0.00)	1.17 (0.00)	1.42 (0.00)
Risk Tolerance	-0.08 (0.00)	0.05 (0.00)	0.05 (0.00)	0.22 (0.00)	0.10 (0.00)	0.45 (0.00)	0.22 (0.00)
Model							
Adj. R^2	.09		.47		.10		.10
Constant	-25.93		-26.83		-28.32		-27.37

Note. All coefficients are significant at $p < 0.001$ level.

Table 3.4 shows the results of the mediation tests. For mediation to be present, the following features must exist. First, household income must be significantly associated with the dependent variable (path *c* in Figure 3.2). Second, household income must be significantly related to risk tolerance (path *a* in Figure 3.2). Third, the effect of household income, when risk tolerance is included as a mediator, must be significantly associated with the dependent variable (path *c'* in Figure 3.2). Fourth, the effect of risk tolerance, in the mediated model, must also be statistically significant (path *b* in Figure 3.2). If the effect of household income on the dependent variable, controlling for risk tolerance, becomes zero, one can conclude that complete mediation is present (Baron & Kenny, 1986). In cases where the effect is different from zero, but still fitting the four requirements described above, partial mediation is assumed to be present. Within these partial mediation models, if the magnitude of the relationship between household income and the dependent variable becomes smaller when risk tolerance is included as a mediator, this is an indication of consistent mediation. If a regression coefficient becomes larger when controlling for risk tolerance, this is referred to as an inconsistent mediation (i.e., a suppressor effect) (MacKinnon et al., 2000). A suppressor variable increases the magnitude of the relationship between the independent and the dependent variable (Conger, 1974; Gaylord-Harden et al., 2010; Tzelgov & Henik, 1991). In other words, if the relationship between household income and the dependent variable in the unmediated model (path *c*) is closer to zero than in the mediated model (path *c'*), this indicates that a mediator is a suppressor variable (MacKinnon et al., 2000; Rucker et al., 2011). A suppression effect can also be present when the direct and mediated effect of the independent variable on the dependent variable have opposite signs, or the direct effect is larger than the total effect in the mediation model (Kenny, 2021; MacKinnon et al., 2007; Rucker et al., 2011). Findings associated with the mediation tests are described below.

Table 3.4. Mediation Tests of Alcohol/Tobacco Use as a Function of Risk Tolerance in Seven Domains

	Participant	Current Drinkers		Current Smokers	
Path	Independent Variable	Dependent Variable	*b*	Dependent Variable	*b*
a	HH Income	R/T_Driving	-0.65	R/T_Driving	-0.65
c	HH Income	Alcohol Use	1.03	Tobacco Use	0.39
c'	HH Income	Alcohol Use	0.20	Tobacco Use	-1.93
b	R/T_Driving		0.09		0.14
a	HH Income	R/T_Finance	0.80	R/T _Finance	0.80
c	HH Income	Alcohol Use	1.03	Tobacco Use	0.39
c'	HH Income	Alcohol Use	0.20	Tobacco Use	-2.68
b	R/T_Finance		0.13		-0.15
a	HH Income	R/T_Occupation	0.02	R/T_Occupation	0.02
c	HH Income	Alcohol Use	1.03	Tobacco Use	0.39
c'	HH Income	Alcohol Use	0.51	Tobacco Use	-2.30
b	R/T_Occupation		0.12		0.01
a	HH Income	R/T_Health	0.10	R/T_Health	0.10
c	HH Income	Alcohol Use	1.03	Tobacco Use	0.39
c'	HH Income	Alcohol Use	0.30	Tobacco Use	-2.63
b	R/T_Health		0.41		0.47
a	HH Income	R/T _Faith	-0.18	R/T_Faith	-0.18
c	HH Income	Alcohol Use	1.03	Tobacco Use	0.39
c'	HH Income	Alcohol Use	0.61	Tobacco Use	-2.45
b	R/T_Faith		0.41		-0.15
a	HH Income	R/T_Relations	0.23	R/T_Relations	0.23
c	HH Income	Alcohol Use	1.03	Tobacco Use	0.39
c'	HH Income	Alcohol Use	0.32	Tobacco Use	-2.41
b	R/T_Relations		0.46		-0.11
a	HH Income	R/T_Life Change	0.16	R/T_Life Change	0.16
c	HH Income	Alcohol Use	1.03	Tobacco Use	0.39
c'	HH Income	Alcohol Use	0.29	Tobacco Use	-2.26
b	R/T_Life Change		0.60		-0.46

Note. Path = Path in Figure 3.2; HH Income = Household Income; R/T = Risk Tolerance. All coefficients are significant at $p < 0.001$ level.

As shown in the first four columns of Table 3.4, risk tolerance was found to be a consistent mediator of alcohol use. The effect of household income on alcohol use was reduced, but greater than zero, when risk tolerance (across the seven risk-taking domains) was included in the models. However, an inconsistent mediation effect was present in relation to household income and tobacco use. Risk tolerance (across the seven risk-taking domains) functioned as a suppressor variable. As shown in Table 3.4, the regression coefficients for household income on tobacco use were larger (in absolute terms) when risk tolerance was included in the regression models. This resulted in a reversal of the income effect where path *c*' (with risk tolerance) has an opposite sign with path *c* (without risk tolerance) in Figure 3.2. Results from the Sobel tests confirmed that the indirect mediated effect of household income on smoking and alcohol use behavior via risk tolerance was significantly different from zero at the alpha level of 0.05. This was true across the seven risk-taking domains.

A robustness check of the findings from the mediation analysis was estimated using a path analysis and a sensitivity analysis (Greenglass & Fiksenbaum, 2009; Imai et al., 2010; Rosenbaum, 2002). The path analysis was used to evaluate the role of household income in describing risk tolerance and tobacco and alcohol use. The model showed the importance of risk tolerance on tobacco and alcohol use. Results from the path analysis confirmed the magnitude and direction of the relationship among household income, risk tolerance, and tobacco and alcohol variables used in the mediation model. The most common sensitivity analysis for causal mediation analysis is based on estimating the correlation between the error for the mediation model and the error for the outcome model (Imai & Yamamoto, 2010). This error correlation serves as the sensitivity parameter. A non-zero sensitivity parameter can be interpreted as evidence for the existence of unobserved confounders that affect both the mediator and outcome (Tingley et al., 2014). Results from the sensitivity analysis showed that the sensitivity parameters ranged from 0 to 0.25 (in absolute values) across the seven domains, indicating little to no error correlation in the models. The sensitivity analysis provided evidence that the core mediation findings were relatively robust to potential violations of the key identifying assumption.

Discussion and Implications

The purpose of this study is to estimate the effect of household income on tobacco and alcohol use and to measure the mediation effect of risk tolerance (across seven risk-taking domains) when describing tobacco and alcohol use. Support was found for the first two research questions that stated household income is negatively associated with tobacco use, and household income is positively associated with alcohol use. Support was also noted for the third and fourth research questions. It was determined that risk tolerance reduces the income effect on alcohol use, primarily through partial/consistent mediation, whereas risk tolerance increases and actually reverses the income effect on tobacco use through partial/inconsistent mediation.

Several implications for those interested in better understanding the interconnections between physical health and personal finance attitudes and behaviors can be drawn from this study. To begin with, the literature does show that tobacco users and those who regularly overindulge in alcohol consumption fail to make, on average, large SES gains over the life course. In some respects, this is due to the substitution effect of income allocation between health-related sensation-seeking expenditures and saving/investing, as well as increased health care costs that result in the deaccumulation of assets over time (O'Neill et al., 2005). Given the relationship between health behaviors and socioeconomic outcomes, the role of personal financial management tools in reducing negative health behaviors is something researchers and policy makers should consider.[12] Among those who smoke tobacco and consume alcohol frequently, any decrease in

[12] According to Baghal (2011), a common debate among researchers and policy makers is the identification of mechanisms used by individuals when establishing and evaluating perceptions of risk related to tobacco use. While some argue that people systematically underestimate the risk associated with smoking (e.g., Romer and Jamieson, 2001), others suggest that risks are often overestimated (Viscusi, 2002). A similar debate exists in relation to alcohol use and abuse (Nolen-Hoeksema, 2004).

these activities should result in an improved financial situation, ceteris paribus, by freeing household income that can be directed towards saving, investing, and debt repayment.

In terms of alcohol use, both income and risk tolerance were, across domains, positively associated with alcohol consumption. This means that someone in this study who was, for instance, more willing to take relationship risks was also likely to report consuming more alcohol than someone who was less willing to take relationship risks. Likewise, a person living in a high-income household was prone to report consuming more alcohol each month. However, each domain of risk tolerance also mediated the income effect on alcohol use. This means that while household income—and by extension SES—was positively associated with alcohol use, the effect was reduced when the model accounted for a survey participant's tolerance for risk. Stated another way, knowing about a person's willingness to take risk appears to be much more important than knowing the person's household income status.

The relationship between risk tolerance and tobacco use was more nuanced. Household income was initially observed to be positively associated with tobacco use across all models. Driving, occupation, and health risk tolerance were also found to be positively associated with tobacco use. However, financial, faith, relationship, and life change risk tolerance were observed to have a negative association with tobacco use. In the mediated models, risk tolerance was found to act as a suppressor variable. This means that risk tolerance reversed the income effect, bringing the income-tobacco use relationship into alignment with what the CDC consistently reports—those with higher household income were found to smoke less. It appears that attitudinal and cognitive appraisals, as a type of predisposing personal characteristic, are a primary descriptor of tobacco use, much more so than household income.

While each risk tolerance measure used in this study was statistically significant, the role of risk tolerance in mediating or suppressing the income effect varied by behavior. In terms of alcohol use, risk tolerance was a consistent mediator. Stated another way, for tobacco use, one should expect a dampening of driving, financial, occupation, health, faith, relationship, and life change risk tolerance to be associated with a reduction in alcohol consumption. In terms of tobacco use, risk tolerance was an inconsistent mediator. One should expect a reduction in driving, occupation, or health risk tolerance to correspond to a reduction in smoking behavior. Conversely, an increase in financial, faith, relationship, or life change risk tolerance should be associated with a decrease in tobacco use. It may be that as tobacco users gain an understanding of the opportunity costs associated with engaging in sensation-seeking behavior, vis-à-vis gains in SES, they elect to reduce tobacco use as their willingness to take risk increases. In this regard, financial professionals can play a key role in promoting healthy behavior and reducing tobacco use among their clients. For example, financial professionals can offer education and resources on the health risk of tobacco use and provide incentives for improved health behaviors. Additionally, financial professionals can assess and monitor clients' risk-taking behavior and encourage healthy lifestyles. In other words, by taking a proactive approach to promoting healthy behaviors, financial professionals can help reduce tobacco use and improve overall health and financial outcomes among their clients.

Over the past four decades, numerous studies have been conducted in an attempt to provide insights into preventing tobacco use among young adults (as well as presenting documentation regarding the negative effects of excess alcohol consumption). Policies that have emerged based on these studies have usually been designed to stop tobacco and excessive alcohol use before behavior begins (Kasperson, 2014). Attempts to curb tobacco and alcohol use among current users tend to rely on medical and mental health treatments (Aksoy et al., 2019) and the use of policies that increase the price of tobacco and alcohol (Gruber & Köszegi, 2004; Haavio & Kotakorpi, 2011; O'Donoghue & Rabin, 2006). While often effective, it may also be possible to help reduce tobacco and alcohol use with non-traditional behavioral and attitudinal interventions. Risk-tolerance education may be such an intervention. Consider the work of Carr et al. (2015). They reported that those who engage in positive cognitive health behavior, such as reading ingredient labels before buying or consuming foods, exhibit better retirement planning behavior compared to those who exercise frequently and/or do not engage in cognitive health activities. Carr et al. (2015) also noted that assessments of risk appear to play a role in explaining why some people engage in cognitive health behavior.

How might risk-tolerance education be delivered? As noted by O'Neill et al. (2005), health and financial education interventions and programs have rarely been presented together. It may be possible to create holistic instructional programs that incorporate aspects of health and financial literacy education. Given the high comorbidity between the two constructs, it is possible that by combining curriculums, attendees will be better able to identify how health behaviors and outcomes are linked with their willingness to take risk, with the result being a change in risk tolerance. Efforts taken to help current alcohol and tobacco users understand and adjust their willingness to take risks across a variety of domains and scenarios may be a pathway to induce a reduction in alcohol and tobacco use. The U.S. Cooperative Extension service is an ideal platform to provide dual-focused education at the community level, especially among low SES groups (Pampel & Rogers, 2004), as are employer-provided benefits classes and high school financial literacy courses.

Limitations

While noteworthy, results from this study should be evaluated in the context of certain limitations. It is important to note, for example, that the results from this study are limited to older tobacco and alcohol users (i.e., those who were aged 54 to 62 as of 2012). It is possible that results for younger individuals might differ from findings reported here. Additionally, the mediation models were, by design, simple. Future studies ought to include other control variables or multiple mediators to account for the possible effect of other participant characteristics and predisposing factors. Future studies should also consider creating a risk-tolerance index or scale that incorporates the seven domains of risk tolerance. Such an index or scale may provide additional insights into the role risk tolerance plays in describing sensation-seeking behavior. Additionally, although the biopsychosocial model of risk-taking argues that predisposing factors, such as household income and risk tolerance, precede the engagement in risk-taking behavior, it is possible that an endogenous relationship between tobacco and alcohol use and household income and risk tolerance exists. Future studies should attempt to decompose these relationships using instrumental variables and expand the scope of this type of study to include longitudinal tracking of NLSY79 study participants.

When viewed holistically in the context of study limitations, the results from this study indicate that risk tolerance appears to be an important predisposing factor, one that is more important than household income alone, in describing tobacco and alcohol use. Risk tolerance meditates (and sometimes suppresses) the income effect on alcohol/tobacco use. Results from this study provide insights that researchers, educators, and policy makers can use to forge a more robust understanding of the association between health behavior and SES.

CHAPTER 4

A COMPARISON OF FINANCIAL RISK TOLERANCE ASSESSMENT METHODS IN PREDICTING SUBSEQUENT RISK TOLERANCE AND FUTURE PORTFOLIO CHOICES

Introduction

Financial risk tolerance refers to someone's willingness to engage in a financial behavior in which the outcome is both uncertain and potentially negative (Nobre & Grable, 2015). A financial advisor who provides investment advice to others for compensation is required, before giving such advice, to first assess the other person's financial risk tolerance. This practice standard is universal. The U.S. Securities and Exchange Commission, the Ontario (Canada) Securities Commission, and the European Securities and Market Authority, certification boards (e.g., CFP Board of Standards, Inc. and the CFA Institute), and self-regulatory organizations (e.g., Financial Industry Regulatory Authority [FINRA]) require financial advisors to assess the willingness and ability of clients to take a financial risk before providing investment advice. The European Securities and Markets Authority (2012) standard is representative of what regulators expect in terms of risk-tolerance assessment: "When providing investment advice or portfolio management the investment firm shall obtain the necessary information regarding the client's or potential client's knowledge and experience in the investment field relevant to the specific type of product or service, that person's financial situation including his ability to bear losses, and his investment objectives including his risk tolerance so as to enable the investment firm to recommend to the client or potential client the investment services and financial instruments that are suitable for him and, in particular, are in accordance with his risk tolerance and ability to bear losses" (n.p.).

While regulators from North America, Europe, Australia/New Zealand, and across Asia mandate that financial advisors assess their clients' risk tolerance, regulators have been reluctant to prescribe how an advisor should actually go about measuring a client's or potential client's willingness to take financial risk. This lack of prescription has led to a proliferation of financial risk-tolerance assessment tools, techniques, tests, quizzes, and scales in the marketplace. Although somewhat simplified, as shown in Figure 4.1, three assessment procedures have come to dominate the marketplace: (1) propensity measurements, (2) stated-preference measurements, and (3) revealed-preference measurements.13 Numerous papers have been published over the past two decades describing the methodological issues associated with the development of reliable and valid measurement tools and the best types of questions to use when assessing risk tolerance (e.g., Guillemette et al., 2012; Roszkowski et al., 2005). Much of the existing literature suggests that few commercial products are fit-for-purpose in the sense of providing an accurate insight into someone's current and future willingness to take a risk (Brayman et al., 2017; Kitces, 2016). The literature is also clear in showing that professional judgment is a weak substitute for a well-designed assessment tool (Roszkowski & Grable, 2005) and that hybrid methods that combine risk-assessment questions with measures of risk capacity, time horizon, and financial decision-maker age, while useful in developing a broader risk profile, can lead to invalid estimates of someone's willingness to engage in risk-taking behaviors (Brayman et al., 2015; Hubble et al., 2020).

[13] Although rarely used in academic settings, some financial advisors use a hybrid assessment approach that relies on stated-preference questions and open-ended questioning.

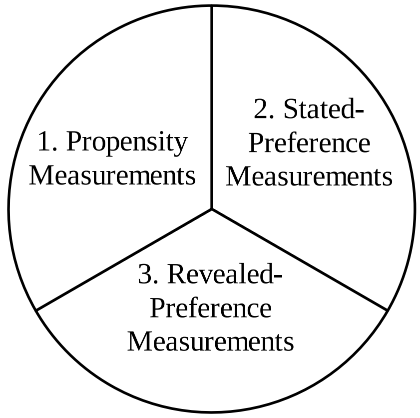

Figure 4.1. Three Primary Risk Tolerance Assessment Methods in the Marketplace

Statement of Purpose

The purpose of this study is to provide policymakers and financial advisors with information that can be used to better understand how a financial decision-maker's willingness to take financial risk can be reliably and validly measured. Specifically, this study is intended to address three issues. The first is to compare the stability of the three primary risk-tolerance assessment methodologies (i.e., propensity, stated-preference, and revealed-preference) across two periods. The second is to identify the factors that can be used to predict changes in risk tolerance across time. The third is to determine which risk-tolerance assessment method offers the best prediction power when describing portfolio choices. The following assumptions were made at the outset of this study: (a) each risk-tolerance method would exhibit some degree of stability across periods, (b) each risk-tolerance assessment method has different factors that can be used to predict the subsequent risk tolerance of financial decision-makers, and (c) each risk-tolerance evaluation method will exhibit a different degree of prediction power in explaining portfolio choices.

Literature Review

The following discussion provides a background review of the three types of financial risk-tolerance assessment methods that were assessed in this study. The review also introduces control variables commonly referenced in the literature whenever financial risk tolerance is evaluated empirically.

Propensity Measures

Propensity measures—sometimes referred to as psychometric tests (Frey et al., 2017)—comprise the largest number of commercial risk-tolerance assessment products in the marketplace. When building a propensity measure, psychometricians assume that decision-makers rely on subjective gain and loss probability estimates when choosing between and among alternatives. Classical test theory is most often used to frame how questions are asked in a propensity measure.[14] Classical test theory is premised on building scales that are reliable and valid (Faff et al., 2009). Reliability refers to the “consistency of individuals’ responses to an instrument across measurement occasions and is a descriptive statistic designed to capture how much measurement error is in a variable” (Beauchamp et al., 2017, p. 205). Validity refers to how well scale scores describe and/or predict behavior (Babbie, 2013). Propensity measures are designed to assess underlying attitudes that prompt behavioral intention and action, and as such, psychometric tests are considered the ‘gold standard’ among those who measure personality, intelligence, and other psychological constructs.

[14] Other psychometric approaches can be used to guide questionnaire development, including item-response theory and Rasch modeling.

Stated-Preference Measures

Sometimes researchers need a straightforward and quick way to assess a decision-maker's willingness to take financial risks. Similarly, from time to time, financial advisors prefer to discuss a client's risk tolerance through a simple question-and-answer format. A stated-preference assessment approach is often used in these situations (Adamowicz et al., 1994). Single-question risk tolerance assessment is, as a result, widely used and trusted by researchers and financial advisors alike. A stated-preference question can be asked this way: "If the markets were to fall by 10%, what would you do?" A stated-preference assessment can also be framed similarly to how risk attitudes are assessed in the Survey of Consumer Finances (SCF): "Which of the following statements comes closest to the amount of financial risk that you are willing to take when you save or make investments?" One drawback associated with single-item stated-preference measures is that reliability tends to fall below that of propensity measures (Grable & Schumm, 2007). Additionally, the validity of scores from stated-preference measures tends to be unstable (Grable & Lytton, 2001).

Revealed-Preference Measures

The primary alternative to propensity and stated-preference measurement techniques is a revealed-preference test. Revealed-preference methodologies are closely aligned with concepts embedded in economic theory. Hanna and Lindamood (2004) argued that "the only rigorous theoretical analyses relating risk tolerance to optimal portfolios are based on the economic concept of risk aversion" (p. 27). To fully understand the difference between a revealed-preference test and a propensity or stated-preference measure, risk and uncertainty must first be differentiated. Weber and Johnson (2009) clarified the difference between these two constructs as follows: "*Risk* refers to situations where the decision-maker knows with certainty the mathematical probabilities of possible outcomes of choice alternatives. *Uncertainty* refers to situations where the likelihood of different outcomes cannot be expressed with any mathematical precision" (p. 132). Those who prefer revealed-preference tests argue that "uncertain situations can be reduced to risky situations" (Weber & Johnson, p. 132). According to Frey and associates (2017), revealed-preference measures are designed to "capture specific cognitive processes, such as the integration of gains and losses or the role of learning and experience" (p. 1). This assessment approach involves having a test taker choose between two outcomes in which the probability of potential gains and losses is known *a priori*. Many revealed-preference assessments have been gamified so that a test taker is presented with numerous choice scenarios. Based on their response, they estimate a risk-preference score. Houthakker (1950) and others (e.g., Weber & Johnson, 2009) argued that revealed-preference scores provide the only valid way to identify a decision-maker's utility function in the domain of investing, which is an essential input into the calculation of constant relative risk aversion (CRRA).

Approaches Compared

There is little consensus concerning which measurement approach is the best. Test developers and psychometricians continue to debate the merits and shortcomings associated with each technique. The principal argument against the use of a propensity scale is that a psychometric test may be little more than a detailed stated-preference assessment. Propensity scores are also difficult to map to a portfolio in the context of the efficient frontier as described in modern portfolio theory. Fischhoff and associates (1978) noted that these limitations do not necessarily diminish the advantages associated with assessing attitudes with propensity measures. Fischhoff et al. argued that, "Attitudes elicited in surveys often correlate highly with behavior … Furthermore, they elicit present values rather than historical preferences" (p. 130). There is some evidence to suggest that propensity measures—at least those developed using psychometric test standards—do a good job of describing and predicting behavior (Dohmen et al., 2011; Lönnqvist et al., 2015).

The obvious weakness associated with the use of stated-preference items is that what a person says they will do does not necessarily correspond to what they do (or will do) in practice. Additionally, the use of stated preferences is almost always premised on the need for a quick response. As such, asking one question when eliciting a risk attitude is common. This approach can result in greater systematic measurement errors and problematic estimates of validity. Although someone's stated preference may do just as well, or possibly better, in accurately describing the person's willingness to take a risk. This possibility has not been fully explored in the literature. However, Grable and Schumm (2007) did show that the reliability of stated-preference items generally fall below standards of acceptability as described by classical test theorists.

The revealed-preference approach is generally considered to be the preferred assessment approach among those trained in economics because it provides the clearest length to descriptions of constant relative risk aversion. This assessment technique, however, is not without its critics. Dow and Werlang (1992) and Hanna et al. (2001) pointed out that revealed-preference tests often fail to provide enough context to lead to a useful response. These researchers also noted that the use of risk, rather than uncertainty, in choice scenarios may not capture the reality of situations faced by financial decision-makers. Additionally, as reported by Barsky et al. (1997) and Charness et al. (2013), asking the average person to make probability choices may be too complex of a task, which often leads to guessing (see also Dave et al., 2010). Lurtz et al. (2021) also suggested that people interpret their own risk tolerance through subjective factors such as thoughts, feeling, values, and life experiences, rather than relying on mathematical calculation when making financial decisions that involve taking risks. In a summary review, Frey et al. (2017) argued that revealed-preference tests may be portraying situational characteristics (i.e., states) that help a person adapt to a particular situation rather than trait factors (Buss, 1989), which are preferences that display consistency across time (Buss, 1989; Josef et al., 2016; Reynaud & Couture, 2012).

One point does tend to generate consensus among researchers: While scores from propensity, stated-preference, and revealed-preference measures tend to correlate positively, the statistical association among these measures tends to be weak (i.e., the effect size of the relationship is generally low). As noted by Frey et al. (2017): "… measures from the propensity and behavioral measurement traditions cannot be used interchangeably to capture risk preference" (p. 8). Results from this study provide evidence to support this assertion.

Other Considerations

Given the complexities associated with measuring financial risk-tolerance attitudes and the possibility that confounding variables may simultaneously influence someone's willingness to take a risk and their engagement in financial behaviors, it is important to account for variables that are known to be associated with risk tolerance and risk-taking behavior whenever descriptive and predictive tests are undertaken (Kaustia & Torstila, 2011). The literature is replete with studies showing the variables most commonly associated with financial risk tolerance. The following discussion highlights some of the most important of these variables, (all of which were controlled for in this study).

Gender. Gender, when measured as self-identifying as a male or female, is known to be related to risk tolerance, with males generally reporting a greater tolerance for risk (Anbar & Eker, 2010; Chavali & Mohanraj, 2016; Grable & Roszkowski, 2007; Hallahan et al., 2004; Larkin et al., 2013).

Age. Age has also been shown to be related to risk tolerance, with older decision-makers generally exhibiting less risk tolerance (Brooks et al., 2018; Gibson et al., 2013; Hallahan et al., 2004; Yao et al., 2011).

Race/Ethnicity. Racial and ethnic background is also thought to be associated with a financial decision-maker's willingness to take financial risks, with those who self-identify as *White/Caucasian* being more risk tolerant compared to those who self-identify as *Black* or *African American* or *Hispanic/Latinx* (Dickason & Ferreira, 2018; Fisher, 2019).

Financial knowledge. A financial decision-maker's knowledge of personal finance concepts has been shown to be positively associated with financial risk tolerance (Gibson et al., 2013; Grable, 2000; Grable & Joo, 2004; Wang, 2009). It is thought that financial knowledge adds to a financial decision-maker's capacity to evaluate risk and endure possible losses associated with investment decisions.

Other factors. Other variables known to be positively associated with financial risk tolerance include household income, education, and wealth status (Hallahan et al., 2004; Pinjisakikool, 2017; Wang et al., 2021; Wong, 2011). Similar to financial knowledge, income, education, and wealth are thought to add to a household's (or financial decision-maker's) risk capacity or their ability to withstand losses associated with financial uncertainty. More inconsistency is related to associations between homeownership and risk tolerance and marital status and risk tolerance (Grable & Joo, 2004; Hallahan et al., 2004; Jianakoplos & Bernasek, 2006; Koekemoer, 2018; Wong, 2011; Yang, 2004). The inconsistency arises because it is unclear if financial decision-makers scale back on risk-taking when the outcomes associated with a risky decision can negatively impact other household members or whether the presence of others in the household enhance risk capacity.

Research Questions

This study was developed to compare propensity, stated-preference, and revealed-preference assessment methodologies. Rather than compare and contrast specific products in the marketplace, the study tests scores from widely used research instruments representing each assessment approach. It is assumed that scores obtained from the instruments are indicative of scoring approaches used by most of the leading marketplace providers of risk-tolerance assessments, as well as being representative of research tests used by those in academia. The following research questions were tested in this study:

RQ_1. How stable is risk tolerance across periods?

RQ_2. What factors can be used to predict the subsequent risk tolerance of a financial decision-maker?

RQ_3. What type of risk-tolerance assessment method offers the best (i.e., most reliable and valid) prediction power when explaining subsequent portfolio choices?

Methods

Data and Risk-Tolerance Measures

Data for this study were obtained from a panel study of 365 individual financial decision-makers. Data were gathered using the online survey panel managed by Dynata (dynata.com).[15] Dynata recruited the sample and distributed Qualtrics questionnaires that included questions used in this study. The delivery of the first and second questionnaires fell approximately six months apart. Respondents completed the first survey in October 2020. The same individuals completed the second survey in March 2021. Each questionnaire took about 15 minutes to complete, with a

[15] A power analysis showed that the sample size was adequate to detect a significant effect with a power level of .80, a significance level of .05, and an effect size of .80 (Aberson, 2019; Cohen, 2013).

standard deviation of five minutes. Those participating in the study received a modest financial incentive after completing each survey. Sample descriptive statistics are shown in Table 4.1.

Three widely used research assessments were used as proxies for propensity, stated-preference, and revealed-preference measures, respectively. Research participants were asked to answer the assessment questions in both surveys. The Grable and Lytton (1999) risk-tolerance scale was used as an indicator of what is generally considered to be a propensity measure. The Grable and Lytton financial risk-tolerance scale, which was developed using concepts from classical test theory, has been widely used as a research instrument in studies designed to evaluate risk-taking attitudes and behaviors (Kuzniak et al., 2015; Lucarelli et al., 2011; Rabbani et al., 2017). The scale consists of 13 multiple-choice questions that are summed to create a score ranging from 13 to 47, with higher scores representing an increased willingness to take financial risk. Across studies and over time, the scale has exhibited acceptable levels of validity (e.g., scores are known to be positively associated with more aggressive investment choices) and reliability (e.g., reported Cronbach's alpha scores have ranged from .70 to over .80, with higher reliability estimates reported for older financial decision-makers (Kuzniak et al., 2015). Propensity scores ranged from 13 to 37 in the first survey (*M* = 24.00, *SD* = 5.19) and 13 to 39 in the follow-up survey (*M* = 24.17, *SD* = 5.40). Cronbach's alpha was .73 in the first survey and .76 in the second survey.

A study participant's stated preference for risk-taking was assessed using the single-time risk-assessment item from the SCF. Participants in the study were asked to respond to the following query:

> "Which of the following statements comes closest to the amount of financial risk that you are willing to take when you save or make investments?" Four answer options will be

> provided: (1) Not willing to take any financial risks; (2) Take average financial risks expecting to earn average returns; (3) Take above-average financial risks expecting to earn above-average returns; and (4) Take substantial risk expecting to earn substantial returns.

Grable and Schumm (2007) estimated the reliability of the SCF item to be approximately .59, which falls below commonly accepted standards for reliability (Nunnally & Bernstein, 1994); nonetheless, this item is the most widely used risk-tolerance (aversion) estimate in the literature primarily because it is included in the Survey of Consumer Finances and many other national and international surveys. Although the reliability falls below evaluation standards, the estimated reliability of the item is relatively robust for a single-item measure. Across both surveys, as shown in Table 4.1, the modal category was to 'take average financial risks expecting to earn average returns.'

The widely used Barsky et al. (1997) revealed-preference test was used as an indicator of commercially available revealed-preference financial risk-tolerance assessments. The Barsky et al. assessment process involves asking study participants to answer the following questions based on a skip pattern choice scenario. Once the questions were answered, a four-point ordinal revealed-preference score was calculated (i.e., high, above-average, below-average, and low-risk tolerance):

> *Question 1: Suppose that you are the only income earner in the family, and you have a good job guaranteed to give you your current (family) income every year for life. You are given the opportunity to take a new and equally good job, with a 50-50 chance it will double your (family) income and a 50-50 chance it will cut your (family) income by a third. Would you take the new job?*

If the answer to this question was ‘yes,’ the participant was then asked:

Question 2: Suppose the chances were 50-50 that it would double your (family) income, and 50-50 that it would cut it in half. Would you still take the new job?

If the answer to the first question was ‘no,’ the participant was then asked:

Question 3: Suppose the chances were 50-50 that it would double your (family) income and 50-50 that it would cut it by 20 percent. Would you then take the new job?

Study participants who answered ‘no’ to the first and third questions were classified as having a low-risk tolerance. A participant who answered 'no' to the first question and 'yes' to the third question was classified as having below-average risk tolerance. A participant who answered ‘yes’ to the first question and ‘no’ to the second question was classified as having above-average risk tolerance. Those who answered ‘yes’ to the first and third questions were classified as having high-risk tolerance. Beauchamp et al. (2017) estimated the reliability coefficient for the Barsky et al. revealed-preference test using polychoric correlations. They estimated reliability to be approximately .59, an estimate that falls below generally recommended scale design guidelines (Nunnally & Bernstein, 1994), but is in alignment with the estimated reliability of the SCF stated-preference question. The modal category across surveys was ‘below average’ in the first survey and ‘low’ in the second survey.

Validity Check

The following question was presented in the second survey and used as a validity check for the risk-tolerance measures:

“Suppose that you were to take a snapshot of your current financial position. Approximately what percent of your total savings and investments are held in stocks or other risky assets (e.g., equity mutual funds)?”

Survey participants were asked to indicate their percentage answer, ranging from zero to 100%, on a sliding scale. It was hypothesized that risk-tolerance scores reported in the first survey should, if valid, predict answers to this question in the second survey. On average, participants held approximately 35% of their portfolios in equities (*Mdn* = 36%, *SD* = 27.31)

Control Variables

As discussed earlier in the paper, nine variables were controlled in the multivariate analyses. The gender of survey participants was assessed by asking each participant to self-identify as *male*, *female*, *non-binary*, or *other*. The sample included only *males* (coded 0) and *females* (coded 1). Self-assessed financial knowledge was determined by asking, "How knowledgeable are you about personal finance topics?" Participants were asked to indicate their knowledge from the following five categories: (1) *not knowledgeable at all*, (2) *slightly knowledgeable*, (3) *moderately knowledgeable*, (4) *very knowledgeable*, and (5) *extremely knowledgeable*. The modal category was 'moderately knowledgeable.' Household income was measured using a 12-point ordinal scale with 1 = *income less than $10,000* and 12 = *more than $150,000*. The modal category was '$70,000 to $79,999'. Education was assessed using an ordinal scale ranging from 1 = *some high school or less* to 6 = *graduate or professional degree*. The modal category was a 'Bachelor's degree.' Wealth status was measured with the following item: "Think about what you own (assets) and what you owe to others (debts and liabilities). If you sold everything you own and paid off all your debts, how much would you have left over?" Participants were asked to select from the following five options: (1) *it would be a large negative number*, (2) *it would be a negative number*, (3) *neither negative nor positive* ($0), (4) *it would be a positive number*, and (5) *it would be a large positive number*. The modal response was 'it would be a positive number' (4). Homeownership was coded dichotomously with 1 = *homeowner*, otherwise 0. Self-identified race/ethnicity was assessed by asking each participant to self-report whether they affiliated as *Caucasian/White*, *African American/Black*, *Hispanic/Latino/Latinx*, *Native American*, *Asian or Pacific Islander*, *or other*. Responses were recoded dichotomously as follows: (a) *Caucasian/White* = 1 (used as reference group), otherwise 0; (b) *African American/Black* = 1, otherwise 0; (c) *Hispanic/Latino/Latinx* = 1, otherwise 0; and (d) *Other*, including *Native American, Asian or Pacific Islander*, or other = 1, otherwise 0. Age was measured categorically beginning at age 18 years (those age 85 or older were used as the reference category). The modal age category was '45 to 54 years'. Marital status was assessed using nominal categories ranging from *never married* to *widowed/other*. Data were coded so that 1 = *married*, otherwise 0 and 1 = *single*, otherwise 0. The reference category was the other classification that included *separated, divorced*, *widowed*, and other study participants.

Data Analysis Methods

Three statistical approaches were used to summarize and analyze the survey data. First, sample descriptive statistics were calculated based on the first survey responses.[16] This was followed by a Spearman correlation analysis showing associations among the three risk-tolerance measures across the first and second surveys. Finally, a series of ordinary least squares and ordinal regression models were estimated to determine the strength of association between risk-tolerance scores from the first survey to scores on the second survey and to determine how well risk-tolerance scores from the first survey predicted portfolio equity holdings at the second survey. The regressions were operationalized as follow.

$$Y_{it+1} = a_0 + a_1 \textit{Risk-Tolerance Score}_{\text{it}} + X_{it}{}'b + \varepsilon_{it+1}$$

[16] Changes in respondent demographic characteristics (e.g., marital status, income, etc.) were evaluated over the two periods. While some respondents did exhibit a changed situation, no significant changes across the sample were noted.

where Y is the risk-tolerance score or portfolio equity holdings, X is a vector of control variables for individual i at time t, b is a vector of coefficients for the control variables, and ε is an error term.

Results

As shown in Table 4.1, the sample was diverse in terms of gender, age, marital status, homeownership, and race/ethnicity. In other respects, those in the sample exhibited relatively high financial knowledge, financial satisfaction, household income, education, and wealth status. The risk tolerance of survey participants fell in the average to the slightly below-average range. Scores on the propensity measure were at the mid-point of the scale across both surveys. Stated-preference scores were relatively stable across the surveys, with the majority of participants indicating below-average or no risk tolerance. Greater variability in revealed-preference score distribution across surveys was observed, with a shift occurring from above-average and high-risk tolerance to below-average and low-risk tolerance**.**

Table 4.1. Sample and Variable Descriptive Statistics (N = 365)

Variable	*M*	*SD*	Percentage
1st Survey Propensity Risk Score	24.13	5.41	
2nd Survey Propensity Risk Score	24.02	5.19	
1st Survey Stated-Preference Risk Score			
None			23%
Below Average			44%
Above Average			28%
High			5%
2nd Survey Stated-Preference Risk Score			
None			22%
Below Average			46%
Above Average			27%
High			5%
1st Survey Revealed-Preference Risk Score			
Low			40%
Below Average			32%
Above Average			17%
High			11%

2nd Survey Revealed-Preference Risk Score			
Low			44%
Below Average			35%
Above Average			9%
High			12%
Portfolio Equity Holdings	35.36	27.31	
Gender			
Male			49%
Female			51%
Subjective Financial Knowledge	3.18	1.04	
Financial Satisfaction	6.78	2.47	
Household Income	7.79	3.55	
Education	4.45	1.39	
Wealth Status	3.98	1.07	
Homeowner			73%
Race/Ethnicity			
White/Caucasian			69%
Black/African American			13%
Hispanic/Latinx			9%
Other Race/Ethnicity			9%
Age			
18 – 24			7%
25 – 34			12%
35 – 44			15%
45 – 54			22%
55 – 64			19%
65 – 74			19%
75 or Older			6%
Marital Status			
Single			33%
Married			54%
Other			13%

Data from Table 4.2 indicate that the associations among the risk-tolerance measurements, across periods, was positive. Each measure was also positively associated with reported portfolio equity holdings in the second survey. This suggests that the three measurement techniques appear to offer some degree of predictive validity in relation to financial decision making, although it is worth noting that the effect size of the relationship between revealed-preference scores and equity holdings, while statistically significant, was not large (Kelley & Preacher, 2012). The correlation coefficients from the table can also be used to gauge the effect size of score associations across the two periods (Cohen, 1992). The relationship between first and second survey propensity scores was quite large. The effect size of the association between the first and second survey stated-preference scores was also large. The effect size of the association between the first and second survey revealed-preference scores was lower (i.e., a medium effect).

Table 4.2. Estimated Associations Between Risk-Tolerance Measures Across Periods

Variable	1	2	3	4	5	6	7
1. 1st Survey PS	1.00						
2. 1st Survey SPS	.53**	1.00					
3. 1st Survey RPS	.36**	.23**	1.00				
4. 2nd Survey PS	.74**	.51**	.28**	1.00			
5. 2nd Survey SPS	.50**	.59**	.24**	.61**	1.00		
6. 2nd Survey RPS	.24**	.17**	.30**	.25**	.15**	1.00	
7. Portfolio Equity Holdings	.41**	.44**	.17**	.49**	.48**	.11*	1.00

Note. PS = Propensity Score; RPS = Revealed-Preference Score; SPS = Stated-Preference Score. *p < .05. **p < .01.

Results from Tables 4.3 and 4.4 provide insight into the question that asked how stable is risk tolerance across periods? Table 4.3 shows the relationship between the first survey propensity scores and subsequent propensity risk-tolerance scores. The propensity model was statistically significant, $F_{20,362} = 27.96$, $p < .001$. The model explained approximately 61% of the variance in propensity risk scores in the second survey ($R^2 = .61$). Risk tolerance from the first period explained the greatest amount of explained variance in subsequent risk-tolerance scores. This indicates that propensity scores were quite stable across the two periods. Other variables of significance in the model included subjective financial knowledge (+), education (+), other race/ethnicity (+), and age categories of 25 to 54 (+), and 75 to 84 (+).

Table 4.3. Regression Showing the Strength of Propensity Scores in Predicting Subsequent Propensity Scores

Variable	*b*	*SE*	*t*
(Constant)	2.27	1.53	1.48
1st Survey Propensity Score	.70**	.04	18.07
Gender (0 = Male; 1 = Female)	-.02	.40	-.04
Subjective Financial Knowledge	.43*	.20	2.13
Financial Satisfaction	-.14	.09	-1.63
Household Income	.08	.07	1.11
Education	.42**	.16	2.71
Wealth Status	-.05	.22	-.24
Homeowner	.61	.51	1.19
Black/African American	.47	.58	.81
Hispanic/Latinx	-.37	.64	-.58
Other Race/Ethnicity	2.15**	.64	3.35
Age			
18 - 24	1.61	1.05	1.54
25 - 34	2.52**	.94	2.69
35 - 44	2.00*	.86	2.33
45 - 54	1.93*	.82	2.35
55 - 64	1.45	.82	1.77
65 -74	.95	.82	1.17
75 - 84	2.20*	1.07	2.06
Single	-.24	.62	-.38
Married	-.06	.58	-.10

*Not*e. **p* < .05. ***p* < .01.

Ordinal regressions were estimated to determine the association between stated- and revealed-preferences and subsequent stated- and revealed-preference scores. The stated-preference model was statistically significant, $\chi^2 = 211.42$, $p < .001$. The model explained approximately 47% of the variance in subsequent stated-preference risk-tolerance scores (Negelkerke $R^2 = .47$). The revealed-preference model was also statistically significant, $\chi^2 = 54.11$, $p < .001$. However, the model explained only 15% of the variance in subsequent revealed-preference risk-tolerance scores (Negelkerke $R^2 = .15$). Table 4.4 shows the results from the regression analyses. The first panel represents estimates for the stated-preference outcome, whereas the second panel represents coefficients for the revealed-preference outcome. Stated-preference scores were positively associated with subsequent risk-tolerance scores, which provided evidence that stated preferences were stable across periods. Other variables of importance in the model included being male (+), subjective financial knowledge (+), and education (+). Only one variable was statistically significant in the revealed-preference model: the first survey revealed-preference scores. The relationship was positive, indicating some degree of stability across periods.

Table 4.4. Stated- and Revealed-Preference Regression Estimates Showing the Strength of Scores in Predicting Subsequent Scores

	Stated-Preference Score			Revealed-Preference Score		
Variable	*b*	*SE*	*t*	*b*	*SE*	*t*
(Constant)	17.21**	6.44	2.54	11.16*	4.98	1.06
1st Survey Score	1.58**	.16	103.08	.60**	.10	34.38
Gender (0 = Male; 1 = Female)	-.56*	.23	5.93	-.07	.21	.12
Subjective Financial Knowledge	.30**	.12	6.76	.15	.11	1.94
Financial Satisfaction	-.03	.05	.44	-.06	.05	1.67
Household Income	.00	.04	.01	.04	.04	.87
Education	.27**	.09	8.70	.09	.09	1.21
Wealth Status	.11	.13	.77	-.19	.12	2.48
Homeowner	.33	.30	1.21	.38	.28	1.82
Black/African American	.55	.33	2.75	.11	.31	.13
Hispanic/Latinx	.27	.36	.55	-.31	.35	.75
Other Race/Ethnicity	.02	.37	.00	-.20	.35	.31
Age						
18 - 24	.20	.60	.11	-.16	.57	.08
25 - 34	.07	.53	.02	-.11	.51	.04
35 - 44	-.55	.49	1.26	-.21	.46	.20
45 - 54	-.30	.47	.42	-.17	.44	.14
55 - 64	-.47	.47	.99	-.01	.44	.00
65 -74	-.90	.47	3.59	-.12	.44	.08
75 - 84	-.39	.61	.40	.63	.57	1.22
Single	-.23	.36	.40	.34	.35	.96
Married	.13	.34	.16	.14	.33	.19

Note. $^*p < .05$. $^{**}p < .01$.

Table 4.5 summarizes the findings from the three regression models. The propensity measure model was the most robust, explaining the greatest amount of variance in subsequent risk-tolerance scores. The stated-preference model also offered a reasonably high degree of outcome explanation. The revealed-preference model was the weakest of the three estimations. A key takeaway from the analyses was that across the variables of interest, first survey risk-tolerance scores were the only common predictor of subsequent risk-tolerance scores. The table also provides an answer to the second research question, which asked what factors can be used to predict the subsequent risk tolerance of a financial decision-maker? Subjective financial knowledge and education level were found to be positively associated with subsequent risk-tolerance scores in the propensity and stated-preference models. Compared to Whites/Caucasians and Blacks/African Americans, those from another racial or ethnic background exhibited greater risk tolerance in the propensity model. Age was also found to be positively associated with risk tolerance in the propensity model. Being male was observed to be positively associated with risk-tolerance in the stated-preference model. None of the control variables in the revealed-preference model were statistically significant.

Table 4.5. Summary of Explanatory Variables Across Measures when Predicting Subsequent Scores

Variable	Propensity Measure	Stated-Preference Measure	Revealed-Preference Measure
1st Survey Risk Score	+	+	+
Gender (Males)		+	
Subjective Financial Knowledge	+	+	
Education	+	+	
Other Race/Ethnicity	+		
Age 25 to 34	+		
Age 35 to 44	+		
Age 45 to 54	+		
Age 75 to 84	+		
R^2	.61	.47	.15

Note. Plus sign (+) = positively associated with the subsequent risk-tolerance score.

Data in Table 4.6 offer answers to the research question that asked, which type of risk-tolerance assessment method offers the best prediction power when describing portfolio choices.

Model A shows that first survey financial risk-tolerance propensity scores positively predicted second-period equity portfolio holdings. Among the variables in the model, the propensity financial risk-tolerance score variable was the most important predictor. Household income and subjective net worth were also found to be positively associated with future equity holdings. Although the coefficients and effect sizes were different, the same pattern of prediction was noted in relation to the stated-preference model (Model B in Table 4.6). Both models explained more than 25% of the variance in second survey equity portfolio holdings. Model C shows the findings from the revealed-preference model. While the first survey revealed-preference scores did positively predict subsequent period equity portfolio holdings, revealed-preference scores were less important than household income, education, and wealth status. This means that the predictive validity of revealed-preference risk-tolerance scores was lower than that of propensity and stated-preference scores. Overall, the revealed-preference model explained approximately 20% of the variance in equity holdings.

Table 4.6. Relationship of Propensity, Stated-Preference, and Revealed-Preference Scores to Portfolio Equity Holdings

Variable	A. Propensity Measure			B. Stated-Preference Measure			C. Revealed-Preference Measure		
	b	*SE*	*t*	*b*	*SE*	*t*	*b*	*SE*	*t*
(Constant)	-45.63**	10.45	.49	-27.33**	9.44	.21	-18.36*	9.98	.30
1st Survey Risk Score	1.77**	.27	.34	11.29**	1.58	.35	2.95*	1.32	.11
Gender (0 = Male; 1 = Female)	.18	2.70	.00	-.74	2.66	-.01	-1.58	2.82	-.03
Sub. Financial Knowledge	.20	1.38	.01	1.10	1.34	.04	2.44	1.40	.09
Financial Satisfaction	.26	.58	.02	.67	.58	.06	.16	.61	.02
Household Income	1.06*	.48	.14	.93	.48	.12	1.36**	.51	.18
Education	1.79	1.06	.09	1.73	1.06	.09	2.53*	1.11	.13
Wealth Status	3.44*	1.48	.14	3.66*	1.46	.14	3.92*	1.55	.15
Homeowner	-.59	3.51	-.01	-1.39	3.49	-.02	.49	3.69	.01
Black/African American	1.53	3.94	.02	1.56	3.91	.02	1.07	4.15	.01
Hispanic/Latinx	5.20	4.30	.06	2.46	4.27	.03	3.95	4.52	.04
Other Race/Ethnicity	1.75	4.39	.02	.52	4.35	.01	.45	4.62	.01
Age									
18 - 24	-6.85	7.16	-.06	-6.16	7.09	-.06	-6.57	7.53	-.06
25 - 34	1.21	6.38	.01	-1.44	6.31	-.02	-1.01	6.71	-.01
35 - 44	-2.60	5.86	-.03	-2.94	5.80	-.04	-6.28	6.14	-.08
45 - 54	3.86	5.62	.06	2.04	5.56	.03	.21	5.90	.00
55 - 64	6.86	5.62	.10	5.17	5.56	.08	2.96	5.89	.04
65 -74	1.52	5.58	.02	.99	5.52	.01	-2.64	5.84	-.04
75 - 84	6.74	7.32	.06	2.69	7.20	.02	.03	7.64	.00
Single	5.74	4.23	.10	2.16	4.22	.04	5.34	4.45	.09
Married	3.41	3.98	.06	.90	3.95	.02	2.21	4.19	.04
	$F_{20,364} = 7.01^{**}$, $R^2 = .28$			$F_{20,364} = 7.44^{**}$, $R^2 = .29$			$F_{20,364} = 4.57^{**}$, $R^2 = .20$		

Note. **p* < .05. ***p* < .01.

Discussion and Implications

This study aimed to compare the three most commonly used risk tolerance assessment methodologies in the marketplace: propensity, stated-preference, and revealed-preference measurement. The goal was to provide financial professionals with a clear understanding of each approach's strengths and weaknesses to enable them to improve their skills when advising clients more effectively. Three widely used research tools, each representing a specific measurement approach, were assessed in relation to describing and predicting subsequent risk-tolerance scores and portfolio holdings. The following three questions were asked: (a) How stable is risk tolerance across periods; (b) What factors can be used to predict the subsequent risk tolerance of a financial decision-maker; and (c) Which type of risk-tolerance assessment method offers the best prediction power when describing portfolio choices?

Each of the measurement approaches exhibited consistency and stability across periods. However, the propensity measure offered the greatest degree of inter-period stability, followed by scores from the stated-preference measure. While the revealed-preference measure exhibited relative stability, revealed-preference scores were the weakest. In this regard, findings from this study support an assertion made by Frey et al. (2017) who argued that "… measures from the propensity and behavioral measurement traditions cannot be used interchangeably to capture risk preference" (p. 8). Correlations among the three measurement approaches were positive, but the effect sizes of the associations ranged from relatively low to high.

Scores from each measurement approach were found to be predictive of subsequent risk-tolerance scores. However, propensity and stated-preference scores were observed to provide a more robust estimate of subsequent risk-tolerance scores compared to revealed-preference scores.

Nonetheless, the tests did show relative stability across periods for the three approaches in predicting future risk attitudes. Similarly, propensity, stated-preference, and revealed-preference scores were found to be predictive of future period equity portfolio holdings. Again, propensity and stated-preference scores provided a more complete picture when making predictions. Household income, education, and wealth status were more important when predicting future equity holdings compared to revealed-preference scores. In other words, gauging a financial decision-maker's income level, educational level, and/or wealth status appears to provide a more robust indication of future equity holdings than a revealed-preference test score.

Of the other variables included in the models, financial knowledge and educational status were important descriptors and predictors of subsequent risk-tolerance. Age, gender (i.e., being male), and other race/ethnicity were also important in some of the prediction models. When predicting future portfolio holdings, in addition to risk-tolerance scores, household income and wealth status were important predictors. Education was significant in the revealed-preference model only. When viewed holistically, these variables represent factors that lead to and support a financial decision-maker's degree of risk capacity (Hubble et al., 2020). As such, it is reasonable to assume that the presence of risk capacity in one period, together with a willingness to take financial risk, can be used to accurately predict future period portfolio choices.

Findings from this study can be used by researchers, financial advisors, and regulators when thinking about the optimal way to evaluate a financial decision maker's willingness to take risks. The three measures used in this study are representative of what is currently offered by vendors. Scores from the propensity measure were the most reliable, stable, and valid followed by stated-preference and revealed-preference scores, respectively. When predicting future portfolio holdings, propensity and stated-preference scores outperformed revealed-preference scores. In this regard, revealed-preference scores, while useful in predicting future investment behavior, were less valuable than household income, wealth status, and education. These findings suggest that if the intention underlying the use of a risk-tolerance assessment is to gain insights into subsequent risk attitudes and investing behavior, a propensity or stated-preference methodology should be given high priority.

As noted at the outset of this paper, regulators from North America, Europe, Australia/New Zealand, and across Asia generally mandate that financial advisors assess the risk tolerance of current and prospective clients. Regulators, however, do not prescribe how a financial advisor ought to go about the measurement of risk. This explains the proliferation of financial risk-tolerance assessment tools, techniques, tests, quizzes, and scales in the marketplace today. Findings from this study provide independent empirical evidence to better understand the strengths and weaknesses associated with propensity measurements, stated-preference assessments, and revealed-preference tests. Results presented in this paper suggest that a propensity approach (i.e., a scale developed using psychometric principles) can be described as being fit-for-purpose if the purpose of the assessment is providing an accurate insight into a financial decision maker's current and future willingness to take a risk. Results also suggest that for those who need a quick and simple indication of subsequent risk tolerance and portfolio allocation behavior, an appropriately worded stated-preference item can be useful. Findings from this study also indicate that while still valid in predicting subsequent risk tolerance and future behavior, scores from revealed-preference tests are the least reliable and valid.

Limitations

While this study fills a gap in the existing literature by following the propensity, stated-preference, and revealed-preference risk tolerance of the same financial decision-makers across periods, and shows that risk-tolerance scores from one period predict future risk tolerance and portfolio choices, results do need to be evaluated in the context of certain limitations. To begin with, the sample was small and likely not generalizable to the U.S. population. Future studies, using larger and more diverse samples, are needed to replicate this study's results. Related to this is the possibility that the choice proxy measures might have influenced results. Had another type of propensity, stated- and/or revealed-preference measure been used, the results might have changed. Additionally, the timing of the study could have had an impact on the way survey participants responded to questions. The initial and follow-up surveys were distributed during the COVID-19 pandemic. Whether this health emergency altered the willingness of financial decision-makers to take financial risk is a topic that warrants future study. Similarly, it is important to acknowledge that the first survey was distributed before the contentious U.S. 2020 presidential election. It is possible that the timing of the survey could have impacted participant preferences and choices. Nonetheless, findings from this study do provide baseline, if exploratory, insights into the stability of financial risk-tolerance across periods and the reliability and validity of commonly used assessment techniques.

CHAPTER 5

CONCLUSION

This dissertation is comprised of three papers to evaluate various aspects of financial risk tolerance—one of the most significant input and output factors in personal financial planning. Each of the papers presented in this dissertation focused on the relationship between risk tolerance and risk-taking behavior, with each paper designed using various types of data from diverse sources, including an experiment, nationally accessible data, and an online survey. Furthermore, the papers utilized unique characteristics and different models appropriate for each data type. Although this dissertation does not provide a comprehensive understanding of financial risk tolerance and risk-taking behavior, the findings from the three papers, when viewed holistically, suggest that financial risk tolerance plays a key role in understanding people's risk-taking behavior. The following conclusion summarizes the important findings from the three papers. The chapter concludes with a presentation of research implications and directions for future research.

Key Findings from Each Study

The first paper in this dissertation evaluated the relationship between brain wave patterns and risk-taking behavior using a quasi-experimental methodology. Specifically, the study aimed to answer the following research questions: (a) do measures of self-assessed financial risk-tolerance and other personal characteristics correlate with engagement in risk-taking behavior, and (b) can alpha, beta, and gamma waves be used to describe who is more or less likely to engage in financial risk-taking decisions? The study’s results indicated that individuals with greater financial knowledge and financial experience were more likely to take the offered risk, while those with greater willingness to take risks were more likely to engage in risk-taking tasks. However, the study showed that alpha, beta, and gamma brain wave activations were not primarily associated with risk-taking behavior. Instead, levels of financial knowledge, financial experience, risk tolerance, and risk aversion were more closely associated with engagement in financial risk-taking behavior.

The second paper aimed to investigate the relationship between household income, risk tolerance, and tobacco and alcohol use among mid-life adults living in the United States, using nationally representative survey data. Specifically, the study was designed to evaluate the mediating effect of risk tolerance on the association between household income and tobacco and alcohol use, and to explore how risk tolerance mediates the income effect for tobacco and alcohol use. The study utilized data collected by the U.S. Bureau of Labor Statistics, which assessed risk tolerance across seven domains of daily life, including driving, financial matters, occupational, health, faith in people, romantic relationships, and major life changes. The results of the study revealed that risk tolerance mediates the relationship between household income and tobacco and alcohol use across the seven domains. Moreover, the study found that risk tolerance had a different relationship in describing the income effect for tobacco and alcohol use. Specifically, risk tolerance functioned as a suppressor variable, mediating the relationship between household income and tobacco use to a greater extent than it did for alcohol use.

The third paper was designed to evaluate the effectiveness of the three primary risk-tolerance assessment methods in describing the risk-taking attitudes and investment behaviors of financial decision-makers across two time periods, using panel data collected via an online survey. The three methods examined were propensity assessments, stated-preference assessments, and revealed-preference assessments. The study results showed that the propensity measure provided the highest degree of consistency across the two time periods, whereas the revealed-preference measure had the weakest consistency. Moreover, the propensity and stated-preference measures provided more substantial predictive power for subsequent risk-taking attitudes and investment behaviors. Furthermore, the study investigated the critical role of demographic variables such as household income, education, and wealth status in predicting subsequent (i.e., post-test) risk tolerance and future equity holdings compared to revealed-preference scores. Study results indicated that these demographic variables play a more important role than revealed-preference scores in predicting subsequent risk attitudes and future equity holdings.

Empirical Contributions

Findings from the three studies provide insight into the way risk-taking behavior is conceptualized by financial decision-makers and ultimately described by researchers. Findings show how the biopsychosocial causal model of risk-taking behavior, which served as the theoretical framework for the second paper, can be expanded to describe multiple forms of risk-taking behavior.

Irwin and Millstein (1986) proposed the biopsychosocial causal model of risk-taking behavior to explain adolescent sensation-seeking behavior. The framework posits that a number of factors act jointly to increase the likelihood of engaging in risk-taking behavior. Specifically, the framework accounts for three types of factors: (1) predisposing endogenous factors, which are unique characteristics to a person (e.g., age, gender, etc.); (2) predisposing exogenous factors, which are behavioral influences arising from external sources (e.g., household income); and (3) precipitating factors, which are psychological and social/environmental factors (e.g., risk tolerance, risk aversion, etc.) that trigger or facilitate risk-taking behavior. Figure 5.1 shows how Irwin and

Millstein's model can be adapted to describe risk-taking behavior exhibited at the household level. Figure 5.1 includes the significant variables identified in the three dissertation studies.

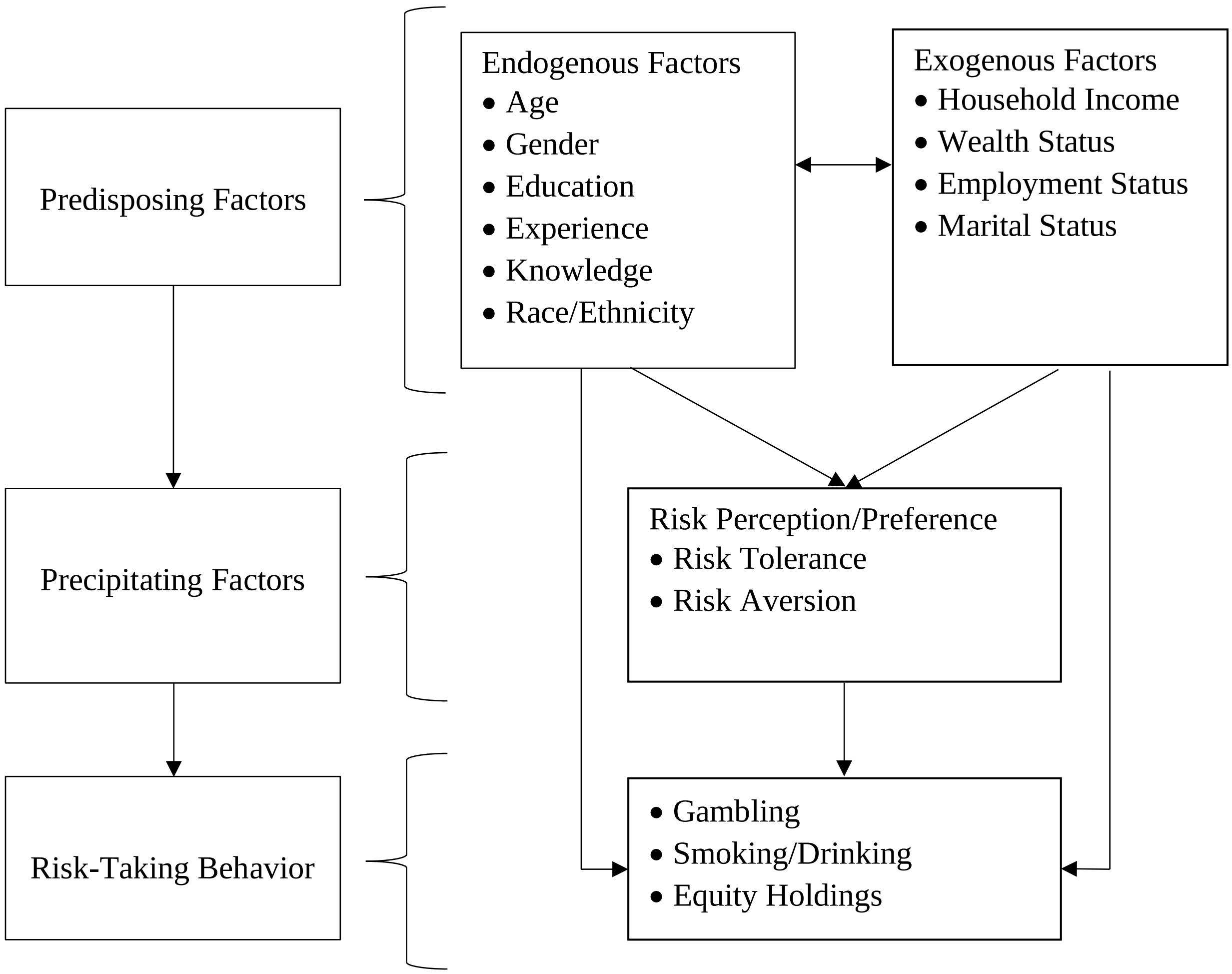

Figure 5.1 The Multi-Factor Model of Household Risk-Taking Behavior (adapted from Irwin & Millstein, 1986).

As shown in Figure 5.1, across the three studies, several predisposing endogenous and predisposing exogenous factors were associated with financial risk tolerance (i.e., a precipitating factor) and risk-taking behavior. In Figure 5.1, risk-taking behavior (RTB) can be modeled as follows:

$$RTB_i = \beta_0 + \sum_{h=1}^{H} \beta_{1,h}\, PreEnd_{i,h} + \sum_{j=1}^{J} \beta_{2,j}\, PreExo_{i,j} + \beta_{3,k} \sum_{k=0}^{K} PreRisk_{i,k} + \varepsilon_i$$

where *PreEnd* represents predisposing endogenous factors, *PreExo* are predisposing exogenous factors, *PreRisk* represents precipitating factors for individual i, and ε is an error term. Note that when $k = 0$, there is no precipitating factor (e.g., risk tolerance, risk aversion, etc.) in the model. In other words, the simplified model, as described in the second study, indicates a direct relationship between predisposing factors and risk-taking behavior without the involvement of a risk tolerance (i.e., mediator) variable.

In alignment with Irwin and Millstein (1986), the model in Figure 5.1 shows that risk-taking behavior is associated with a variety of personal and environmental factors. The model also illustrates that descriptions of risk-taking behavior are complex, with most descriptive variables being interrelated and mediated through a financial decision-maker's willingness to take a risk.

Findings from the first study show that the difference between a risk seeker and a risk avoider can be explained by the person's financial experience and financial knowledge (i.e., predisposing endogenous factors), and their willingness to take a risk (i.e., precipitating factors). The person's innate tolerance for risk (i.e., a predisposing trait-like factor) primes a financial decision-maker to engage in a risk-taking task. Risk seekers appear to react with less cognitive effort. Findings from the first study show that a risk seeker does not need to be as cognitively engaged in the risk-taking decision process. Risk avoidance behavior, on the other hand, is associated with elevated levels of brain activation, particularly among those with lower levels of financial knowledge, financial experience, and risk tolerance. In order to encourage a risk avoider to take a financial risk, it may be necessary to reduce stimuli and moderate cognitive responses.

Considering the second study, risk tolerance, as a precipitating factor—a personal or environmental characteristic that either directly or indirectly influences behavior—acts as a mediator between predisposing endogenous and exogenous factors and risk-taking behavior. As a mediator, risk tolerance changes the effect of certain predisposing endogenous factors and predisposing exogenous factors as they relate to risk-taking behavior. Stated another way, while predisposing endogenous factors and predisposing exogenous factors often directly relate to risk-taking behavior, these same variables are also indirectly associated with risk-taking behavior through risk tolerance.

The multi-factor model of household risk-taking behavior can serve as a useful tool for financial planners, researchers, and policymakers when considering a client's personal and environmental characteristics during the data-gathering phase of the financial planning and financial counseling process. Furthermore, the model also provides a framework for developing research models and formulating policies aimed at influencing household risk-taking behavior. As shown in Figure 5.1, risk tolerance, or a person's willingness to engage in a behavior in which the outcome is both uncertain and potentially negative, plays an important role in describing risk-taking behavior. Risk tolerance, as a precipitating factor, acts directly on a financial decision-makers' intention to take risks as well as a mediator of factors related to the engagement in risk-taking behavior. It is recommended that future research be conducted to more fully assess the model shown in Figure 5.1.

Implications

Although framed with a personal finance and financial planning lens, findings from this dissertation have implications for research, policy, and practice that extends beyond the domain of financial planning. The three papers presented in this dissertation provide insights into the relationship between financial risk-taking attitudes and risk-taking behavior, along with the way certain personal characteristics are related to risk-taking behavior. The dissertation illustrates how various data-gathering approaches, including experimental, secondary data, and primary panel online survey data methods, can be utilized to provide greater insight into how financial decision-makers incorporate their willingness to take a risk into daily risk-taking behavior.

Findings from the studies comprising this dissertation can assist financial planners, financial counselors, and financial professionals in evaluating clients' financial situations and understanding financial matters in a way that allows financial advisors to make better-informed recommendations as a pathway to helping clients reach their financial goals. Additionally, findings from the studies can be applied to improve the way risk attitudes are evaluated and incorporated into financial planning, policy, and research models that focus on risk-taking behavior. Understanding individual decision-maker attitudes and behaviors, as well as the relationship between the two, can aid in providing better financial advice and guidance, education planning, and policy directives. The following discussion highlights how each paper can inform practice, policy, and research.

Paper One

The first paper in this dissertation examined the use of personal characteristics, cognitive activity (brain waves), and attitudinal factors in describing risk-taking behavior. Through the use of an EEG methodology to measure cognitive activities beyond a survey response, which has yet to be explored in the financial planning research area, this study expands the risk-tolerance and risk-taking literature in a way that shows how cognitive variables, in addition to personal characteristics, can be used to describe and predict behavior. When comparing the factors analyzed between a risk taker and a risk avoider in financial risk-taking situations, the results of this study suggest that risk-taking behavior is more closely associated with personal characteristics, such as financial knowledge, financial experience, and financial risk attitude (i.e., risk tolerance and aversion), rather than primarily brain wave activation. Additionally, brain wave activation resulting from engagement in a risk-taking task appears to be more directly in alignment with the level of financial knowledge, financial experience, risk tolerance, and risk aversion exhibited by a financial decision-maker.

The findings from the first study have several implications for those who provide financial advice to others as a professional activity. When financial service professionals present risky choices and options to clients, they should consider the financial knowledge and experience of their client as key factors in recommending a choice for the client's financial situation. Furthermore, the level of the client's willingness to take a risk, as well as their unwillingness to take a risk, should be considered when making a recommendation. Providing context for the assortment of risky option alternatives appears to be an important element in guiding clients to a meaningful choice. Regarding the study's methodology, results show that the use of EEG and brain wave analyses has enormous potential as a clinical and research tool for better understanding risk-taking behavior. The study showed that cognitive activations when facing financial choices involving the possibility of uncertain gains and losses are important when describing financial behavior (although it is important to note that factors such as risk tolerance do appear to prime certain cognitive activations).

Paper Two

The second study presented in this dissertation examined the extent to which risk tolerance serves as a mediator in the relationship between household income and tobacco and alcohol use. This study makes a unique contribution to the literature on financial counseling and planning, financial education, and financial therapy, as well as public policy, by exploring whether risk tolerance, as a perception, attitude, or cognitive appraisal of risk, mediates the effects of income on negative health behaviors. Although numerous studies have investigated the association between household income, risk-taking health behaviors, and risk tolerance, this study is distinct in its use of mediation analysis, using risk tolerance as a mediator, to assess the unparalleled role of risk tolerance in reducing negative behaviors that have a detrimental impact on people's health. Moreover, the study revealed the different roles of risk tolerance in describing tobacco and alcohol use, further advancing the literature in the domains of financial counseling and planning, financial education, financial therapy, and public policy.

The results of the second study in this dissertation have implications for financial planners, financial counselors, financial therapists, and those involved in shaping public policy as results provide a better understanding of the interconnections between health and personal finance behaviors. As noted in the paper, health and financial issues are inherently intertwined, with healthcare costs being a significant challenge for those tasked with the financial management of households. Financial issues often also lead to health problems, particularly for those in low socioeconomic situations. A key takeaway from the paper is that the use of personal financial management tools can help reduce negative health behaviors and improve household financial situations by reducing spending on tobacco and alcohol consumption, leading to improved health behaviors and outcomes. In terms of improving someone's negative health behaviors, it is more important to utilize a person's willingness to take risks, defined as their perception of risk, than to explore their household income status, which may be more difficult to change than the perception of risk, especially for those living in lower-income households. In other words, financial planners, financial counselors, financial therapists, and policymakers can help those who smoke and drink alcohol overcome problematic health behaviors by adopting risk education as a tool for cognitive training to induce positive change related to health-related behaviors.

Paper Three

The third paper in this dissertation was designed to address several gaps in the existing literature on personal financial planning, specifically with regard to financial risk tolerance and its relationship with investment behaviors. The study compared the consistency of three financial risk-tolerance assessment methods primarily used by financial planners, financial counselors, and other financial service professionals. The study examined the value of three risk-tolerance (risk aversion) assessment methods across two time periods using panel data. The study also investigated which assessment method was better for predicting investment behavior and risk attitudes in a post-test follow-up. The study's unique design, which relied on panel data, makes significant contributions to the body of knowledge in personal financial planning by moving the literature away from merely describing differences in assessment methodologies based on cross-sectional data to the use of panel data.

Findings from this study have significant implications for financial planners, financial counselors, and other financial professionals in relation to assessing a financial decision-maker's willingness to take risks. Measuring financial risk tolerance is a crucial element that needs to be evaluated based on a targeted time and purpose. By providing a comprehensive assessment of the strength and weaknesses of the three most commonly used financial risk tolerance methods in personal financial planning, this paper provides evidence as to which assessment technique offers the most robust level of predictive validity when working with financial decision-makers.

The study's results suggest that the propensity measure exhibited greater consistency compared to the other risk tolerance measures (e.g., stated-preference and revealed-preference measures) across the two surveys. In addition, the propensity measure demonstrated stronger predictive power in relation to subsequent risk tolerance and equity holdings. Considering the results, financial professionals seeking a consistent (i.e., reliable), valid, and predictive financial risk-tolerance measurement method that provides essential insights into a financial decision-maker's future investment behavior should choose a propensity measurement tool. On the other hand, if a quick and straightforward method of measuring a client's financial risk tolerance is required, a stated-preference measure can be used, as it requires a single question. It is essential to note, however, that the stated-preference measure will almost always be less reliable and valid over time compared to a propensity measurement. If a financial service professional is looking for a tool that is closely related to economic theory, a revealed-preference measure can be used; however, if a revealed-preference test is utilized, certain limitations must also be accepted, including less reliable and valid scoring. Results from the study suggest that financial service professionals should carefully consider the purpose when selecting a financial risk-tolerance measurement method. They should also be aware of the strengths and weaknesses of each method before selecting the most appropriate one for use in practice. By doing so, they can provide valuable insights to their clients and make better informed financial decisions that enhance client goal achievement.

Future Research Directions

There are several areas for future research that can build upon the work presented in this dissertation. First, future research should consider employing larger and more diverse samples, particularly in relation to experimental and direct survey data collection methods. Doing so will make research findings more generalizable. Although the studies presented in this dissertation have uncovered significant insights into the relationships between financial risk tolerance and risk-taking behavior, larger samples are needed in replications to ensure that findings are generalizable outside of what tend to be relatively homogenous subsets of the population (e.g., residents of small communities, investors, etc.). Increasing sample diversity could be further enhanced through the use of longitudinal studies. A longitudinal survey would allow researchers to examine whether the results obtained in this dissertation hold over time. Longitudinal studies could also shed light on how risk-taking behavior changes over longer periods, while also providing a platform to identify factors that influence or cause changes in behavior that cannot be captured by a single survey or experiment. Overall, such studies can provide more generalized insights and advance the field's understanding of the complex relationships between financial risk tolerance and risk-taking behavior.

Future research studies should also focus on developing comprehensive or multimodal models for research. The studies in this dissertation offer a unique perspective on the relationship between financial risk tolerance and risk-taking behavior. Building on the results and findings of the studies in this dissertation, researchers can create more advanced models by incorporating other variables that play different roles in describing a particular relationship or by utilizing various research models to reflect more realistic situations in the daily lives of financial decision-makers. Researchers can also use multimodal approaches for this purpose. For example, regarding the first study in this dissertation, by utilizing multiple methodologies such as eye tracking, heart rate variability, and fMRI, future research can compare results and justify findings in a more generalized manner. This can also help researchers identify the key factors that influence or interact with each other under realistic circumstances, thereby facilitating a better understanding of risk-taking behavior, as well as providing better predictions of future behaviors.

Lastly, to gain a comprehensive understanding of people's risk-taking behavior across diverse scenarios, it is essential to analyze and apply factors from various disciplines, such as psychology, neuroscience, and economics. Understanding a given financial situation is not just one-sided. Instead, it requires incorporating various perspectives from different aspects using a multidimensional viewpoint. Researchers can use the findings from the studies in this dissertation as a guide to adopting an interdisciplinary approach when collaborating with experts in different fields to gain a better comprehension of how behaviors are shaped and influenced. This can be facilitated by using multiple theoretical and methodological lenses with multiple layers of analysis.

Conclusion

In conclusion, this dissertation contributes to the literature on financial planning, financial counseling and education, and financial therapy by illustrating how different data collection modalities and varying methodological tools and techniques can be used to frame research questions related to the factors that are crucial in comprehending and describing risk-taking behavior in their everyday lives of financial decision-makers. By acknowledging the relationship and unique roles of numerous factors that are related to (and sometimes explain) risk-taking behavior, financial planners, financial advisors, and other financial service professionals, as well as researchers and policymakers, can take evidence-based steps in understanding their clients' circumstances, analyzing financial matters, and providing the most appropriate recommendations to achieve a client's financial goals throughout the financial planning process in an effective way.

REFERENCES

Aberson, C. L. (2019). *Applied power analysis for the behavioral sciences* (2nd ed.). Routledge.

Adamowicz, W., Louviere, J., & Williams, M. (1994). Combining revealed and stated preferences methods for valuing environmental amenities. *Journal of Environmental Economics and Management, 26*, 271-292.

Altman, M. (2010). Prospect theory and behavioral finance. In H. K. Baker & J. R. Nofsinger (Eds.), *Behavioral finance*. (pp. 191-210). Wiley.

Aminoff, M. J. (2012). Electroencephalography: General principles and clinical applications. In M. J. Aminoff (Ed.), *Aminoff's electrodiagnosis in clinical neurology* (6th ed., pp. 37–84). Elsevier.

Anbar, A., & Eker, M. (2010). An empirical investigation for determining the relation between personal financial risk tolerance and demographic characteristic. *Ege Akademik Bakis Dergisi, 10*, 503-522.

Auld, M. C. (2005). Smoking, drinking, and income. *Journal of Human Resources*, *40*(2), 505-518. https://doi.org/10.3368/jhr.XL.2.505

Babbie, E. (2013). *The practice of social research* (13th ed.). Belmont, CA: Wadsworth Cengage Learning.

Badcock, N. A., Mousikou, P., Mahajan, Y., de Lissa, P., Thie, J., & McArthur, G. (2013). Validation of the emotive EPOC® EEG gaming system for measuring research quality auditory ERPs. *PeerJ, 1*, e38. https://doi.org/10.7717/peerj.38

Balaz, S, Stepan, C., Binder, H., von Gizycki, H., Avitable, M, Obersteiner, A., Rattay, F., Selesnick, I., & Bodis-Wollner, I. (2006). Conjugate eye movements and gamma power modulation of the EEG in persistent vegetative state. *Journal of the Neurological Sciences, 246*, 65–69.

Baron, R. M., & Kenny, D. A. (1986). The moderator–mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, *51*(6), 1173-1182. https://doi.org/10.1037/0022-3514.51.6.1173

Barsky, R. B., Juster, F. T., Kimball, M. S., & Shapiro, M. D. (1997). Preference parameters and behavioral heterogeneity: An experimental approach in the health and retirement study. *The Quarterly Journal of Economics, 112*, 537-579.

Bartley, M. (2019). Poverty and health inequality. In B. Greve (Ed.), *Routledge International Handbook of Poverty* (pp. 351-362). Routledge.

Başar-Eroglu, C., Strüber, D., Schürmann, M., Stadler, M., & Başarb, E. (1996). Gamma-band responses in the brain: A short review of psychophysiological correlates and functional significance. *International Journal of Psychophysiology, 24*, 101–112.

Bastos, N. S., Adamatti, D. F., & Billa, C. Z. (2016). Discovering patterns in brain signals using decision trees. *Computational Intelligence and Neuroscience*, *2016*, 1–10.

Beauchamp, J. P., Cesarini, D., & Johannesson, M. (2017). The psychometric and empirical properties of measures of risk preference. *Journal of Risk and Uncertainty, 54*, 203-237.

Bertrand, O., & Tallon-Baudry, C. (2000). Oscillatory Gamma activity in humans and its role in object representation. *International Journal of Psychophysiology, 38*, 211–223.

Blais, A-R., & Weber, E. U. (2006). A domain-specific risk-taking (DOSPERT) scale for adult populations. *Judgment and Decision Making, 1*, 33–47.

Blakely, T., Hales, S., Kieft, C., Wilson, N., & Woodward, A. (2005). The global distribution of risk factors by poverty level. *Bulletin of the World Health Organization, 83*, 118-126.

Blow, F. C., & Barry, K. L. (2012). Alcohol and substance misuse in older adults. *Current Psychiatry Reports*, *14*(4), 310-319.

Blume, J. H., & Paavola, E. C. (2011). Life, death, and neuroimaging: The advantages and disadvantages of the defense's use of neuroimages in capital cases—Lessons from the front. *Cornell Law Faculty Publications, Paper 212*. http://scholarship.law.cornell.edu/facpub/212

Bogan, V. L., & Fertig, A. R. (2013). Portfolio choice and mental health. *Review of Finance*, 17, 955-992.

Booth, L. (2004). Formulating retirement targets and the impact of time horizon on asset allocation. *Financial Service Review*, *13*(1), 1-18.

Braver, T. S., & Barch, D. M. (2002). A theory of cognitive control, aging cognition, and neuromodulation. *Neuroscience & Biobehavioral Reviews, 26*(7), 809-817.

Brayman, S., Finke, M., Bessner, E., Grable, J., Griffin, P., & Clement, R. (2015). *Current practices for risk profiling in Canada and review of global best practices.* Research report prepared for the Investor Advisory Panel of the Ontario Securities Commission. https://memofin-media.s3.eu-west-3.amazonaws.com/Documents/0001/06/61b6c58de96a9ea8fe0b6386e8daa5992060eb97.pdf

Brayman, S., Grable, J. E., Griffin, P., & Finke, M. (2017). Assessing a client's risk profile: A review of solution providers. *Journal of Financial Service Professions*, *71*(1), 71-81.

Brooks, C., Sangiorgi, I., Hillenbrand, C., & Money, K. (2018). Why are older investors less willing to take financial risk? *International Review of Financial Analysis*, *56*, 52-72.

Brüggen, E. C., Hogreve, J., Holmlund, M., Kabadayi, S., & Löfgren, M. (2017). Financial well-being: A conceptualization and research agenda. *Journal of Business Research*, *79*, 228-237.

Buss, D. M. (1989). Conflict between the sexes: Strategic interference and the evocation of anger and upset. *Journal of Personality and Social Psychology*, *56*(5), 735-747.

Callan, V. J., & Johnson, M. (2002). Some guidelines for financial planners in measuring and advising clients about their levels of risk tolerance. *Journal of Personal Finance*, *1*(1), 31-44.

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics. *Journal of economic Literature*, *43*(1), 9-64.

Carr, N. A., Sages, R. A., Fernatt, F. R., Nabeshima, G. G., & Grable, J. E. (2015). Health information search and retirement planning. *Journal of Financial Counseling and Planning*, *26*(1), 3-16.

Cavanagh, J. F., Frank, M. J., Klein, T. J., & Allen, J. J. (2010). Frontal theta links prediction errors to behavioral adaptation in reinforcement learning. *Neuroimage, 49*(4). 3198-3209.

Center for Disease Control and Prevention. (2019). *Chronic diseases in America*. https://www.cdc.gov/chronicdisease/resources/infographic/chronic-diseases.htm

Chang, C. C., DeVaney, S. A., & Chiremba, S. T. (2004). Determinants of subjective and objective risk tolerance. *Journal of Personal finance, 3*(3), 53-67.

Charness, G., Gneezy, U., & Imas, A. (2013). Experimental methods: Eliciting risk preferences. *Journal of Economic Behavior & Organization, 87*, 43-51.

Chavali, K., & Mohanraj, M. (2016). Impact of demographic variables and risk tolerance on investment decisions: An empirical analysis. *International Journal of Economics and Financial Issues, 6*, 169-175.

Chen, Y., & Wallraven, C. (2017). Pop or not? EEG correlates of risk-taking behavior in the balloon analogue risk task. *2017 5th International Winter Conference on Brain-Computer Interface (BCI), 2017*, 16-19.

Christopoulos, G. I., Tobler, P. N., Bossaerts, P., Dolan, R. J., & Schultz, W. (2009). Neural correlates of value, risk, and risk aversion contributing to decision making under risk. *Journal of Neuroscience*, *29*(40), 12574-12583.

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences* (3rd ed.). Routledge.

Collins, S. E. (2016). Association between socioeconomic factors and alcohol outcomes. *Alcohol Research: Current Reviews, 38*(1), 83-94.

Coquelet, C., Granié, M. A., & Griffet, J. (2019). Conformity to gender stereotypes, motives for riding and aberrant behaviors of French motorcycle riders. *Journal of Risk Research*, *22*(8), 1078-1089.

Cordell, D. M. (2002). Risk tolerance in two dimensions. *Journal of Financial Planning, 15*(4), 30-35.

Dave, C., Eckel, C. C., Johnson, C. A., & Rojas, C. (2010). Eliciting risk preferences: When in simple better? *Journal of Risk and Uncertainty*, *41*, 219-243.

Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*, 9–21.

Delorme, A., Sejnowski, T., & Makeig, S. (2007). Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis. *Neuroimage*, *34*(4), 1443–1449.

Demos, J. H. (2005). *Getting Started with Neurofeedback*. Norton.

Dickason, Z., & Ferreira, S. J. (2018). Gender and behavior: The effect of gender and ethnicity on financial risk tolerance in South Africa. *Gender and Behaviour*, *16*, 10851-10862.

Dohmen, T., Falk, A., Huffman, D., Sunde, U., Schupp, J. U., & Wagner, G. G. (2011). Individual risk attitudes: Measurement, determinants, and behavioral consequences. *Journal of the European Economic Association*, *9*, 522-550.

Dow, J., & Werlang, S. R. D.C. (1992). Uncertainty aversion, risk aversion, and the optimal choice of portfolio. *Econometrica*, *60*, 197-204.

Droms, W. G., & Strauss, S. N. (2003). Assessing risk tolerance for asset allocation. *Journal of Financial Planning*, *16*(3), 72-77.

Eberhardt, W., de Bruin, W. B., & Strough, J. (2019). Age differences in financial decision making: The benefits of more experience and less negative emotions. *Journal of behavioral decision making*, *32*(1), 79-93.

European Securities and Markets Authority (2018). *General Guidelines*. https://www.esma.europa.eu

Faff, R., Hallahan, T., & McKenzie, M. (2009). Nonlinear linkages between financial risk tolerance and demographic characteristics. *Applied Economics Letters, 16*, 1329-1332.

Fecteau, S., Knoch, D., Fregni, F., Sultani, N., Boggio, P., & Pascual-Leone, A. (2007). Diminishing risk-taking behavior by modulating activity in the prefrontal cortex: A direct current stimulation study. *Journal of Neuroscience*, *27*(46), 12500-12505.

Financial Industry Regulatory Authority. (2012, July 9). *Additional guidance on FINRA's new suitability rule, Regulatory notice 12-25.* https://www.finra.org/rules-guidance/notices/12-25

Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., & Combs, B. (1978). How safe is enough? A psychometric study of attitudes towards technological risks and benefits. *Policy Sciences*, *9*, 127-152.

Fisher, P. (2019). Black-White differences in financial risk tolerance. *Journal of Financial Service Professionals*, *73*(4), 70-82.

Fisher, P. J., & Yao, R. (2017). Gender differences in financial risk tolerance. *Journal of Economic Psychology*, *61*, 191-202.

Frey, R., Pedroni, A., Mata, R., Rieskamp, J., & Hertwig, R. (2017). Risk preference shares the psychometric structure of major psychological traits. *Science Advances*, *3*(10), e1701381. https://doi.org/ 10.1126/sciadv.1701381

Gratton, G., Cooper, P., Fabiani, M., Carter, C., & Karayanidis, F. (2017). Dynamics of cognitive control: Theoretical bases, paradigms, and a view for the future. *Psychophysiology*, *55*(3), 1-29.

Gianotti, L. R., Knoch, D., Faber, P. L., Lehmann, D., Pascual-Marqui, R. D., Diezi, C., Schoch, C., Eisenegger, C., & Fehr, E. (2009). Tonic activity level in the right prefrontal cortex predicts individuals' risk taking. *Science, 299*, 1898–1902.

Gibson, R. J., Michayluk, D., & Van de Venter, G. (2013). Financial risk tolerance: An analysis of unexplored factors. *Financial Services Review, 22*, 23-50.

Grable, J. E. (2000). Financial risk tolerance and additional factors that affect risk taking in everyday money matters. *Journal of Business and Psychology*, *14*(4), 625-630. https://doi.org/10.1023/A:1022994314982

Grable, J. E., & Chatterjee, S. (2022). Defining personal finance. In J. E. Grable & S. Chatterjee (Eds.), *Handbook of Personal Finance*. (pp. 3-17). De Gruyter.

Grable, J. E., & Joo, S-H. (2004). Environmental and biopsychosocial factors associated with financial risk tolerance. *Journal of Financial Counseling and Planning*, *15*(1), 73-82.

Grable, J. E., & Lytton, R. H. (1999). Financial risk tolerance revisited: The development of a risk assessment instrument. *Financial Services Review*, *8*, 163-181.

Grable, J. E., & Lytton, R. H. (2001). Assessing the concurrent validity of the SCF risk assessment item. *Journal of Financial Counseling and Planning, 12(*2), 43-52.

Grable, J. E., & Rabbani, A. (2014). Risk tolerance across life domains: Evidence from a sample of older adults. *Journal of Financial Counseling and Planning*, *25*(2), 174-183.

Grable, J. E., & Roszkowski, M. J. (2007). Self-assessment of risk tolerance by women and men. *Psychological Reports, 100*, 795-802.

Grable, J. E., & Schumm, W. (2007). An estimate of the reliability of the Survey of Consumer Finances risk-tolerance question. *Journal of Personal Finance, 9*, 117-131.

Grable, J. E., Heo, W., & Rabbani, A. G. (2014). Financial anxiety, physiological arousal, and planning intention. *Journal of Financial Therapy, 5*(2), 1–18.

Grable, J. E., Kwak, E-J, Fulk, M., & Routh, A. (2020). A Simplified measure of investor risk aversion. *Journal of Interdisciplinary Economics, 33*(1), 1–28. https://journals.sagepub.com/doi/pdf/10.1177/0260107920924518.

Grafova, I. B. (2011). Financial strain and smoking. *Journal of Family and Economic Issues, 32*, 327-340. https://doi.org/10.1007/s10834-011-9247-2

Greenglass, E. R., & Fiksenbaum, L. (2009). Proactive coping, positive affect, and well-being. Testing for mediation using path analysis. *European Psychologist*, *14*(1), 29-39.

Gonzalez-Prendes, A. A., & Resko, S. M. (2012). Cognitive-Behavioral theory. In S. Ringel, & J. Brandell (Eds.), *Trauma: Contemporary Direction in Theory, Practice, and Research (*1st ed., pp.14-40). SAGE Publications, Inc.

Guillemette, M. A., Finke, M., & Gilliam, J. (2012). Risk tolerance questions to best determine client portfolio allocation preferences. *Journal of Financial Planning, 25*(5), 36-44.

Gutter, M. S., Hayhoe, C. R., DeVaney, S. A., Kim, J., Bowen, C. F., Cheang, M., Cho, S. H., Evans, D. A., Gorham, E., Lown, J. M., Mauldin, T., Solheim, C., Worthy, S. L., & Dorman, R. (2012). Exploring the relationship of economic, sociological, and psychological factors to the savings behavior of low-to moderate-income households. *Family and Consumer Sciences Research Journal*, *41*(1), 86-101.

Hallahan, T. A., Faff, R. W., & McKenzie, M D. (2004). An empirical investigation of personal financial risk tolerance. *Financial Services Review, 13*, 57-78.

Hammond, K. R., & Summers, D. A. (1972). Cognitive control. *Psychological Review*, *79*(1), 58-67.

Hanna, S. D. & Lindamood, S. (2004). An improved measure of risk aversion. *Journal of Financial Counseling and Planning*, *15*(2), 27-45.

Hanna, S. D., Gutter, M. S., & Fan, J. X. (2001). A measure of risk tolerance based on economic theory. *Journal of Financial Counseling and Planning*, *12*(2), 53-60.

Hanna, S. D., Waller, W., & Finke, M. (2008). The concept of risk tolerance in personal financial planning. *Journal of Personal Finance*, *7*(1), 96-108.

Hanoch, Y., Johnson, J.G., & Wilke, A. (2006). Domain specificity in experimental measures and participant recruitment: An application to risk-taking behavior. *Psychological Science*, *17*, 300-304.

Heo, W. (2019). The way consumers and clients respond to financial conversations: Investigation with measurement of EEG signals. 2019 Academic Research Colloquium for Financial Planning and Related Disciplines. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3257637

Hiscock, R., Bauld, L., Amos, A., Fidler, J. A., & Munafò, M. (2012). Socioeconomic status and smoking: A review. *Annals of the New York Academy of Sciences*, *1248*(1), 107-123. https://doi.org/10.1111/j.1749-6632.2011.06202.x

Hong, E., & Hanna, S. D. (2014). Financial planning horizon: A measure of time preference or a situational factor? Journal of Financial Counseling and Planning, 25(2), 184-196.

Hong, G., Qin, X., & Yang, F. (2018). Weighting-based sensitivity analysis in causal mediation studies. *Journal of Educational and Behavioral Statistics*, *43*(1), 32-56.

Horvath, P., & Zuckerman, M. (1993). Sensation seeking, risk appraisal, and risky behavior. *Personality and Individual Differences*, *14*(1), 41-52. https://doi.org/10.1016/0191-8869(93)90173-Z

Horvitz, D. G., & Thompson, D. J. (1952). A generalization of sampling without replacement from a finite universe. *Journal of the American Statistical Association*, *47*(260). 663-685.

Houthakker, H. S. (1950). Revealed preference and the utility function. *Economica, 17,* 159-174.

Hubble, A., Grable, J. E., & Dannhauser, B. (2020). Investment Risk Profiling: A Guide for financial advisors. *CFA Institute.* https://www.cfainstitute.org/en/research/industry-research/investment-risk-profiling

Imai, K., Keele, L., & Yamamoto, T. (2010). Identification, inference, and sensitivity analysis for causal mediation effects. *Statistical Science*, *25*(1), 51-71.

Imai, K., & Yamamoto, T. (2010). Causal inference with differential measurement error: Nonparametric identification and sensitivity analysis. *American Journal of Political Science, 54*(2), 543-560.

Irwin, C. E., & Millstein, S. G. (1986). Biopsychosocial correlates of risk-taking behaviors during adolescence: Can the physician intervene? *Journal of Adolescent Health Care, 7*(6), 82-96.

James, L. R., & Brett, J. M. (1984). Mediators, moderators, and tests for mediation. *Journal of Applied Psychology*, *69*(2), 307. https://doi.org/10.1037/0021-9010.69.2.307

Jebelli, H., Hwang, S., & Lee, S. (2016). An EEG signal-processing framework to obtain high-quality brain waves from an off-the-shelf wearable EEG device. *Journal of Computing in Civil Engineering, 32*(1), 04017070.

Jebelli, H., Hwang, S., & Lee, S. (2018). EEG-based workers' stress recognition at construction sites. *Automation in Construction, 93*, 315–324.

Jianakoplos, A., & Bernasek, A. (2006). Financial risk taking by age and birth cohort. *Southern Economic Journal, 72*, 981-1001.

Joseph, A. K., Richter, D., Samanez-Larkin, G. R., Wagner, G. G., Hertwig, R., & Mata, R. (2016). Stability and change in risk-taking propensity across the adult life span. *Journal of Personality and Social Psychology, 111*, 430-450.

Judd, C. M., & Kenny, D. A. (1981). Process analysis: Estimating mediation in treatment evaluations. *Evaluation Review*, *5*(5), 602-619. https://doi.org/10.1177/0193841X8100500502

Kahneman, D. (2011). *Thinking, Fast and Slow*. Farrar, Straus and Giroux.

Kahneman, D., & Tversky, A. (1979). Prospect theory—analysis of decision under risk. *Econometrica, 47*, 263–292.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1990). Experimental tests of the endowment effect and the Coase theorem. *Journal of Political Economy*, *98*(6), 1325–1348.

Kaustia, M., & Torstila, S. (2011). Stock market aversion? Political preferences and stock market participation. *Journal of Financial Economics*, *100*(1), 98-112.

Kitces, M. (2016, September 14). The sorry state of risk tolerance questionnaires for financial advisors. *Nerd's Eye View Blog*. https://www.kitces.com/blog/risk-tolerance-questionnaire-and-risk-profiling-problems-for-financial-advisors-planplus-study/

Knetsch, J. L. (1989). The endowment effect and evidence of nonreversible indifference curves. *The American Economic Review, 79*(5), 1277–1284.

Koekemoer, Z. (2018). The influence of demographic factors on risk tolerance for South African investors. *Proceedings of the International Academic Conferences*, 6408640, International Institute of Social and Economic Sciences.

Kohler, M. P. (1996). Risk-taking behavior: A cognitive approach. *Psychological Reports*, *78*(2), 489-490.

Kotte, S., & Dabbakuti, J. K. (2020). Methods for removal of artifacts from EEG signal: A review. *Journal of Physics: Conference Series*, *1706*(1).

Krawczyk, D. (2002). Contributions of the prefrontal cortex to the neural basis of human decision making. *Neuroscience & Biobehavioral Reviews*, *26*(6), 631-664.

Krompinger, J. W., Moser, J. S., & Simons, R. F. (2008). Modulations of the electrophysiological response to pleasant stimuli by cognitive reappraisal. *Emotion*, *8*(1). 132-137.

Kropotov, J. D. (2009). *Quantitative EEG, Event-Related Potentials and Neurotherapy*. Elsevier.

Kuhnen, C., & Knutson, B. (2005). The neural basis of financial risk taking. *Neuron*, *47*(5), 763-770.

Kuzniak, S., Rabbani, A. G., Heo, W., Ruiz-Menjivar, J, & Grable, J. E. (2015). The Grable and Lytton risk-tolerance scale: A 15-year retrospective. *Financial Services Review, 24*, 177–192.

Larkin, C., Lucey, B. M., & Mulholland, M. (2013). Risk tolerance and demographic characteristics: Preliminary Irish evidence. *Financial Services Review, 22*, 77-91.

Lee, T., Girolami, M., & Sejnowski (1999). Independent component analysis using an extended informax algorithm for mixed sub-gaussian and super-gaussian sources. *Neural Computation*, *22*(2), 417-441.

Lee, Y. G., & Kim, S. S. (2017). Gender and risk-bearing portfolio choices among older single workers: The role of human capital. *Family and Consumer Sciences Research Journal*, *45*(4), 406-421.

Loewenstein, G. F., Weber, E. U., Hsee, C. K., & Welch, N. (2001). Risk as feelings. *Psychological bulletin*, *127*(2), 267.

Lohr, S. L. (2021). *Sampling: Design and analysis* (3rd ed.). CRC Press.

LÖnnqvist, J-E., Verkasalo, M., Walkowitz, G., & Wichardt, P. C. (2015). Measuring individual risk attitudes in the lab: Task or ask? An empirical comparison. *Journal of Economic Behavior & Organization, 119*, 254-266.

Lucarelli, C., Ottaviani, C., & Vandone, D. (2011). The layout of the empirical analysis. In C Lucarelli & G. Brighetti (Eds.), *Risk tolerance in financial decision making* (pp. 153-180). Palgrave MacMillan.

Lurtz, M. R., Archuleta, K., Kothakota, M., & Jorgensen, T. J. (2021). A deeper dive: A mixed methods approach to risk tolerance. *Financial Planning Review*, *4*, e1112.

Maciejewski, M. L. (2020). Quasi-experimental design. *Biostatistics & Epidemiology*, *4(*1), 38-47.

Manning, W. G., Keeler, E. B., Newhouse, J. P., Sloss, E. M., & Wasserman, J. (2013). The external costs of smoking and heavy drinking. *The costs of poor health habits*. Harvard University Press. https://doi.org/10.4159/harvard.9780674422261

Marmot, M. (2002). The influence of income on health: Views of an epidemiologist. *Health Affairs, 21*(2), 31-46.

Martos, C. (2021, February 15). Brain-behavior relationship: Are we our brains? *Neuronup*. https://neuronup.us/cognitive-stimulation-news/brain/brain-and-behavior-relationship/

Mata, R., Frey, R., Richter, D., Schupp, J., & Hertwig, R. (2018). Risk preference: A view from psychology. *Journal of Economic Perspectives, 32*, 155–172.

Mokdad, A. H., Marks, J. S., Stroup, D. F., & Gerberding, J. L. (2004). Actual causes of death in the United States, 2000. *Journal of the American Medical Association, 291*, 1238-298.

Moyer, R. M., & Song, G. (2019). Cultural predispositions, specific affective feelings, and benefit–risk perceptions: explicating local policy elites' perceived utility of high voltage power line installations. *Journal of Risk Research*, *22*(4), 416-431.

Neumann, N., Sterhl, U., Birhaumer, N., & Kotchoubey, B. (2016). Electroencephalographic measures and biofeedback. In M. S. Schwartz & A. Frank (Eds.), *Biofeedback: A practitioner's guide* (4th ed., pp. 98–112). The Guilford Press.

Noble, N., Paul, C., Turon, H., & Oldmeadow, C. (2015). Which modifiable health risk behaviours are related? A systematic review of the clustering of Smoking, Nutrition, Alcohol and Physical activity ('SNAP') health risk factors. Preventive medicine, 81, 16-41.

Nobre, L. H. N., & Grable, J. E. (2015). The role of risk profiles and risk tolerance in shaping client decisions. *Journal of Financial Service Professionals, 69*(3), 18-21.

Nunnally, J., & Bernstein, L. (1994). *Psychometric theory*. McGraw-Hill.

Nusslock, R., Young, C. B., Pornpattananangkul, N., & Damme, K. S. F. (2015). Neurophysiological and neuroimaging techniques. In R. L. Cautin & S. O. Lilienfeld (Eds.), *The encyclopedia of clinical psychology*. Wiley-Blackwell. https://doi.org/10.1002/9781118625392.wbecp557

O'Neill, B. (2005). Health and wealth connections: Implications for financial planners. *Journal of Personal Finance, 4*(2), 27-39. https://search.proquest.com/docview/198919194

O'Neill, B. (2009). Health and wealth connections: Evidence from research and practice. *Journal of Family and Consumer Sciences, 101*(3), 14-19. https://search.proquest.com/docview/218152086

O'Neill, B., Sorhaindo, B., Xiao, J. J., & Garman, E. T. (2005). Financial distressed consumers: Their financial practices, financial well-being, and health. *Journal of Financial Counseling and Planning, 16*(1), 73-87. https://digitalcommons.uri.edu/hdf_facpubs/8/

Paek, H-J., and Hove, T. (2017). *Risk perceptions and risk characteristics*. London: Oxford Research Encyclopedias. https://doi.org/10.1093/acrefore/9780190228613.013.283

Pampel, F. C., & Rogers, R. G. (2004). Socioeconomic status, smoking, and health: A test of competing theories of cumulative advantage. *Journal of Health and Social Behavior, 45*, 306-321. https://doi.org/10.1177/002214650404500305

Pampel, F. C., Krueger, P. M., & Denney, J. T. (2010). Socioeconomic disparities in health behaviors. *Annual Review of Sociology, 36*, 349-370.

Perry, V. G., & Morris, M. D. (2005). Who is in control? The role of self-perception, knowledge, and income in explaining consumer financial behavior. *Journal of Consumer Affairs, 39*(2), 299-313. https://doi.org/10.1111/j.1745-6606.2005.00016.x

Pinjisakikool, T. (2017). The influence of personality traits on households' financial risk tolerance and financial behavior. *Journal of Interdisciplinary Economics, 30*, 32-54.

Pollack, C. E., Chideya, S., Cubbin, C., Williams, B., Dekker, M., & Braveman, P. (2007). Should health studies measure wealth? A systematic review. *American Journal of Preventative Medicine, 33*, 250-264. https://doi.org/10.1016/j.amepre.2007.04.033

Porter, S. N. (2019). Poverty, Discrimination, and Health. In D. F. Pacquiao (Ed.), *In Social pathways to health vulnerability* (pp. 23-53). New York: Springer.

Pulvermüller, F., Birbaumer, N., Lutzenberger, W., & Mohr, N. (1997). High-frequency brain activity: Its possible role in attention, perception and language processing. *Progress in Neurobiology*, *52*, 427–445.

Rabbani, A. G., & Nobre, L. H. N. (2022). Financial risk tolerance. In J. E. Grable & S. Chatterjee (Eds.), *Handbook of Personal Finance*. (pp. 137-156). De Gruyter.

Rabbani, A. G., Grable, J. E., Heo W., Nobre, L., & Kuzniak, S. (2017). Stock market volatility and changes in financial risk tolerance during the Great Recession. *Journal of Financial Counseling and Planning*, *28*(1), 140–154.

Rabbani, A. G., Yao, Z., Wang, C., & Grable, J. E. (2020). Financial risk tolerance, sensation seeking, and locus of control among pre-retiree baby boomers. *Journal of Financial Counseling and Planning*, *32*(1), 146-157.

Rasheed, R., & Siddiqui, S. H. (2018). Attitude for inclusive finance: influence of owner-managers' and firms' characteristics on SMEs financial decision making. *Journal of Economic and Administrative Sciences*.

Reynaud, A., & Couture, S. (2012). Stability of risk preference measures: Results from a field experiment on French farmers. *Theory and Decision*, *73*, 203-221.

Roeder, J., Palmer, M., & Muntermann, J. (2022). Data-driven decisionmaking in credit risk management: The information value of analyst reports. *Decision Support Systems*, 113770.

Roohi-Azizi, M., Azimi, L., Heysieattalab, S., & Aamidfar, M. (2017). Changes of the brain's bioelectrical activity in cognition, consciousness, and some mental disorders. *Medical Journal of the Islamic Republic of Iran, 31*, 53–58.

Rosen, H. S., & Wu, S. (2004). Portfolio choice and health status. *Journal of Financial Economics, 72*, 457-484.

Rosenbaum, P. R. (2002). *Design of observational studies*. New York: Springer.

Ross, C., & Wu, C. L. (1995). The links between education and health. *American Sociological Review, 60*, 719-745. https://doi.org/10.2307/2096319

Roszkowski, M. J., & Grable, J. E. (2005). Estimating risk tolerance: The degree of accuracy and the paramorphic representations of the estimate. *Journal of Financial Counseling and Planning, 16*(2), 29-48.

Roszkowski, M. J., Davey, G., & Grable, J. E. (2005). Insights from psychology and psychometrics on measuring risk tolerance. *Journal of Financial Planning, 18(*4), 68-76.

Rowan, J. A., & Tolunsky, E. (2003). *Primer of EEG with a mini-atlas.* Elsevier.

Rudorf, S., Preuschoff, K., & Weber, B. (2012). Neural correlates of anticipation risk reflect risk preferences. *The Journal of Neuroscience, 32*, 16683–16692.

Sadi, R., Asl, H. G., Rostami, M. R., Gholipour, A., & Ghlipour, F. (2011) Behavioral finance: The explanation of investors' personality and perceptual biases effects on financial decision. *International Journal of Economics and Finance, 3*(5), 234-241.

Sanei, S., & Chambers, J. A. (2013). *EEG signal processing.* John Wiley & Sons Ltd.

Sazgar, M., & Young, M. G. (2019). Overview of EEG, electrode placement, and montages. In M. Sazgar & M. G. Young (Eds.), *Absolute epilepsy and EEG rotation review* (pp. 117–125). Springer.

Smith, D. M., Langa, K. M., Kabeto, M. U., & Ubel, P. A. (2005). Health, wealth, and happiness: Financial resources buffer subjective well-being after the onset of a disability. *Psychological Science, 16*, 663-666. https://doi.org/10.1111/j.1467-9280.2005.01592.x

Sobel, M. E. (1982). Asymptotic confidence intervals for indirect effects in structural equation models. *Sociological Methodology*, *13,* 290-312. https://doi.org/10.2307/270723

Sobel, M. E. (1986). Some new results on indirect effects and their standard errors in covariance structure models. *Sociological methodology*, *16*, 159-186. https://doi.org/10.2307/270922

Steriade, M. (2006). Grouping of brain rhythms in corticothalamic systems. *Neuroscience, 137*, 1087–1106.

Studer, B., Pedroni, A., & Rieskamp, J. (2013). Predicting risk-taking behavior from prefrontal resting-state activity and personality. PLoS ONE, 8(10), e76861.

Sturm, R. (2002). The effect of obesity, smoking, and drinking on medical problems and costs. *Health Affairs*, *21*(2), 245-253.

Szrek, H., Chao, L. W., Ramlagan, S., & Peltzer,K. (2012). Predicting (un)healthy behavior: A comparison of risk-taking propensity measures. *Judgment and Decision Making, 7,* 716-727.

Thaler, R. (1980). Toward a positive theory of consumer choice. *Journal of Economic Behavior and Organization*, *1*(1), 39–60.

Thatcher, R. W. (2016). Quantitative encephalography and electroencephalographic biofeedback/neurofeedback. In M. S. Schwartz & A. Frank (Eds.), *Biofeedback: A practitioner's guide* (4th ed., pp. 113–127). The Guilford Press.

Tingley, D., Yamamoto, T., Hirose, K., Keele, L., & Imai, K. (2014). Mediation: R package for causal mediation analysis. *Journal of Statistical Software, 59*(5), 1-38.

Trimpop, R. M. (1994). *The psychology of risk-taking behavior*. Elsevier.

Tversky, A., & Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk Uncertainty, 5*, 297–323.

Valaskova, K., Bartosova, V., & Kubala, P. (2019). Behavioural aspects of financial decisions-

Van Cott, A., & Brenner, R. P. (1998). Technical advantages of digital EEG. *Journal of Clinical Neurophysiology, 15*, 464–475.

Vanderwolf, C. H. (2000). Are neocortical Gamma waves related to consciousness? *Brain Research, 855*, 217–224.

Viola, F. C., Debener, S., Thorne, J., & Schneider, T. R. (2010). Using ICA for the analysis of multi-channel EEG data. In M. Ullsperger., & S. Debener (Eds.), *Simultaneous EEG and fMRI: Recording, analysis, and application* (pp. 121-133). Oxford University Press.

Walsh, JL., Senn. TE., & Carey, MP. (2013). Longitudinal association between health behaviors and mental health in low-income adults. *Translational Behavioral Medicine, 3*(1), 104-113.

Wang, A. (2009). Interplay of investors' financial knowledge and risk taking. *Journal of Behavioral Finance*, *10*, 204-213.

Wang, F., Li, H., & Wang, Q. (2021). Risk tolerance and household wealth—evidence from Chinese households. *Economic Modelling, 94*, 885-895.

Warschauer, T. (2002). The role of universities in the development of the personal financial planning profession. Financial Services Review, 11(3), 201.

Weber, E. U., & Johnson, E. J. (2009). Decisions under uncertainty: Psychological, economic, and neuroeconomic explanations of risk preference (pp. 127-144). In P. W. Glimcher, C. F. Camerer, E. Fehr, & R. A. Poldrack (Eds.), *Neuroeconomics: Decision making and the brain*. Elsevier.

Weber, E.U., Blais, A. R., & Betz, N.E. (2002). A domain-specific risk-attitude scale: Measuring risk perceptions and risk behaviors. *Journal of Behavioral Decision Making, 15*, 263-290.

Wei, H., Zhone, Z., Yang, L., Yao, T., Huang, S., & Mao, X. (2020). Impact of smoking on the income level of Chinese urban residents: A two-wave follow-up of the China family panel study. *BMJ Open Journal, 10*(8). http://doi.org/10.1136/bmjopen-2020-036939

Wong, A. (2011). Financial risk tolerance and selected demographic factors: A comparative study in 3 countries. *Global Journal of Finance & Banking Issues, 5*(5), 1-12.

Wong, A., & Carducci, B. J. (1991). Sensation seeking and financial risk taking in everyday money matters. *Journal of business and psychology*, *5*(4), 525-530.

Worthy, S. L., Jonkman, J., & Blinn-Pike, L. (2010). Sensation-seeking, risk-taking, and problematic financial behaviors of college students. Journal of Family and Economic Issues, 31(2), 161-170.

Wright, J. (2017). *To what extent does income predict an individual's risk profile in the UK (2012 – 2014)* (MPRA Paper No. 80757). Munich Personal RePEc Archive. https://mpra.ub.uni-muenchen.de/80757/

Yan, J., & Brocksen, S. (2013). Adolescent risk perception, substance use, and educational attainment. *Journal of Risk Research*, *16*(8), 1037-1055.

Yang, Y. (2004). Characteristics of risk preferences: Revelations from Grable & Lytton's 13-item questionnaire. *Journal of Personal Finance, 3*(3), 20-40.

Yao, R., & Curl, A. L. (2011). Do market returns influence risk tolerance? Evidence from panel data. *Journal of Family and Economic Issues*, *32*(3), 532-544.

Yao, R., Sharpe, D. L., & Wang, F. (2011). Decomposing the age effect on risk tolerance. *The Journal of Socio-Economics*, *40*, 879-887.

Zagorsky, J. L. (2005). Health and wealth: The late 20th century obesity epidemic in the U.S. *Economics and Human Biology, 3*, 296-313. https://doi.org/10.1016/j.ehb.2005.05.003

Zelazo, P. D., & Anderson, J. E. (2013). What is cognitive control. In P. D. Zelazo, & M. D. Sera (Eds.), *Minnesota Symposia on Child Psychology (*Volume 37., pp.1-20). Wiley.

Zhu, T., Chen, Y., Asante, E., Zhu, Y., & Xu, T. (2022). How does leader humility influence team creativity? The roles of team behavioral integration and leader performance, *Frontiers in Psychology*, 13:818865.

Zinn, J. O. (2019). The meaning of risk-taking—key concepts and dimensions. *Journal of Risk Research, 22*(1), 1-15.

Zuckerman, M. (1979). *Sensation seeking: Beyond the optimal level of arousal*. Erlbaum.

Zuckerman, M. (1983). *Biological bases of sensation seeking, impulsivity and anxiety*. Erlbaum.